Current and Potential Robotic Applications to Improve Cotton Production

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Abstract

Rapid advances in computer vision, deep learning, and autonomous equipment have resulted in commercial robots for autonomous weed control and point to a future where robotic systems will play a larger role in agricultural production. Over the last two years, Cotton Incorporated has sponsored projects to look at the potential use of robots for cotton harvest and more recently, weed control. These projects have collectively resulted in an autonomous robot capable of traveling through the field using a combination of proximal sensors and GPS; a small tractor using machine vision that can autonomously harvest cotton bolls under defoliated conditions; a draft economic model that incorporates regional climate data to compare the value of a robotic harvest system to once-over harvesters; and data from plots in four locations where cotton was hand-harvested twice per week to estimate the potential yield and quality benefits of frequent harvest events to provide estimates for the economic model. Initial progress has also been made in evaluating new mechanism for removing seed cotton from the plant, developing an image library of weed species significant to cotton, exploration of genetic manipulations that could facilitate robotic harvest, and concepts around material handling in the field. In addition to providing an overview of recent progress, this paper will also explore other areas of cotton production that could benefit from the use of robotic systems. Ultimately the goal of these projects is to make it easier for those companies developing autonomous agricultural equipment and machine vision applications adapt their systems for use by cotton producers.[1]

[1] *Presented at the 2020 Beltwide Cotton Conferences, Austin, TX. Jan. 8-10, 2020. National Cotton Council, Memphis, TN.*

Contents

Introduction

Rapid advances in the technologies of machine vision, computer processing, and controls have led to several companies announcing agricultural robotic systems, including applications for weed control, row crop planting, and fruit and vegetable harvest (e.g., https://builtin.com/robotics/farming-agricultural-robots). The concept of robotic applications is not new, with Sistler (1987) providing a review of robotic applications and future possibilities over three decades ago. The dairy industry has rapidly adopted robotics for milking cows, and Salfer et al. (2019) estimate over 35,000 robotics milking systems are currently in use globally. For row crops, much of the commercial focus is on weed control with the rise of herbicide resistant weeds and lack of new herbicide modes of action (Westwood et al., 2018). Most of the major agricultural machinery companies have announced autonomous machinery plans, have prototype machines and/or have filed patents on autonomous robotic systems for agriculture (e.g., Murray et al., 2018). The concept of an autonomous platform with several interchangeable implements is emerging as a preferred concept for agricultural robots (Feldschwarm ® technologies: http://www.feldschwarm.de; Dot Power Platform: https://seedotrun.com/).

Barnes et al. (2019) discussed how the ability to conduct multiple harvests after first open boll could improve fiber quality and reduce yield loss due to extreme weather events. The objective of this paper is to provide an update and overview of current projects working on robotic systems for cotton production and speculate about additional future applications beyond weed control and harvest.

Robotic Project Updates – Progress on Cotton Harvest and Weed Control

In 2019, Cotton Incorporated sponsored projects at Texas A&M, the University of Georgia (UGA), and Clemson University to evaluate robotic platforms for cotton harvest. Clemson and UGA were also tasked to address robotic weed control along with collaboration from North Carolina State University. Scientists at the University of North Texas examined the possibility of genetically modifying the plant architecture to simplify robotic harvest. Economists at Kansas State University made significant progress on an economic model to compare robotic harvest system configurations to the current one-pass harvest system. To have data on the potential impact of frequent harvest to support the economic model, field studies where cotton were hand-harvested twice weekly was conducted by Texas A&M (two locations), University of Georgia, and University of Tennessee. Updates on most of these projects are included in the following sections.

Approaches for Boll Identification and Removal (Texas A&M University)

A key requirement of a robotic cotton harvester is an appropriate end effector. Lab tests were conducted to estimate the power requirements for a suction end effector and found a minimum of 1kW was required. Because solar-recharged batteries would be ideal for multiple field robots, this level of power requirements appears to be excessive for in-field solar robots. Multiple potential versions of an energy-efficient end effector based on mechanical picking have been

considered. Each of these would require doffing and transfer of picked seed-cotton. A challenge for both suction and mechanical approaches is the cotton boll orientation. Three potential solutions exist to deal with this issue: (1) utilizing a high degree of freedom manipulator that can face cotton boll along with artificial intelligence to calculate control actions; (2) adding auxiliary components to the end effector to force the cotton boll change its orientation; and (3) designing an end effector that can pick seed cotton without considering cotton boll orientation. A combination of these solutions is also possible. Major orientations have been categorized for cotton bolls on a plant (Figure 1), and a preliminary design of a five-spindle end effector developed (Figure 2). This design has two main limitations: (1) sometimes the spindle may not pick all the seed-cotton; and (2) seed-cotton wound on two or more spindles could cause problems; e.g., a branch could get stuck among the spindles, keeping the end effector from being pulled away from the plant.

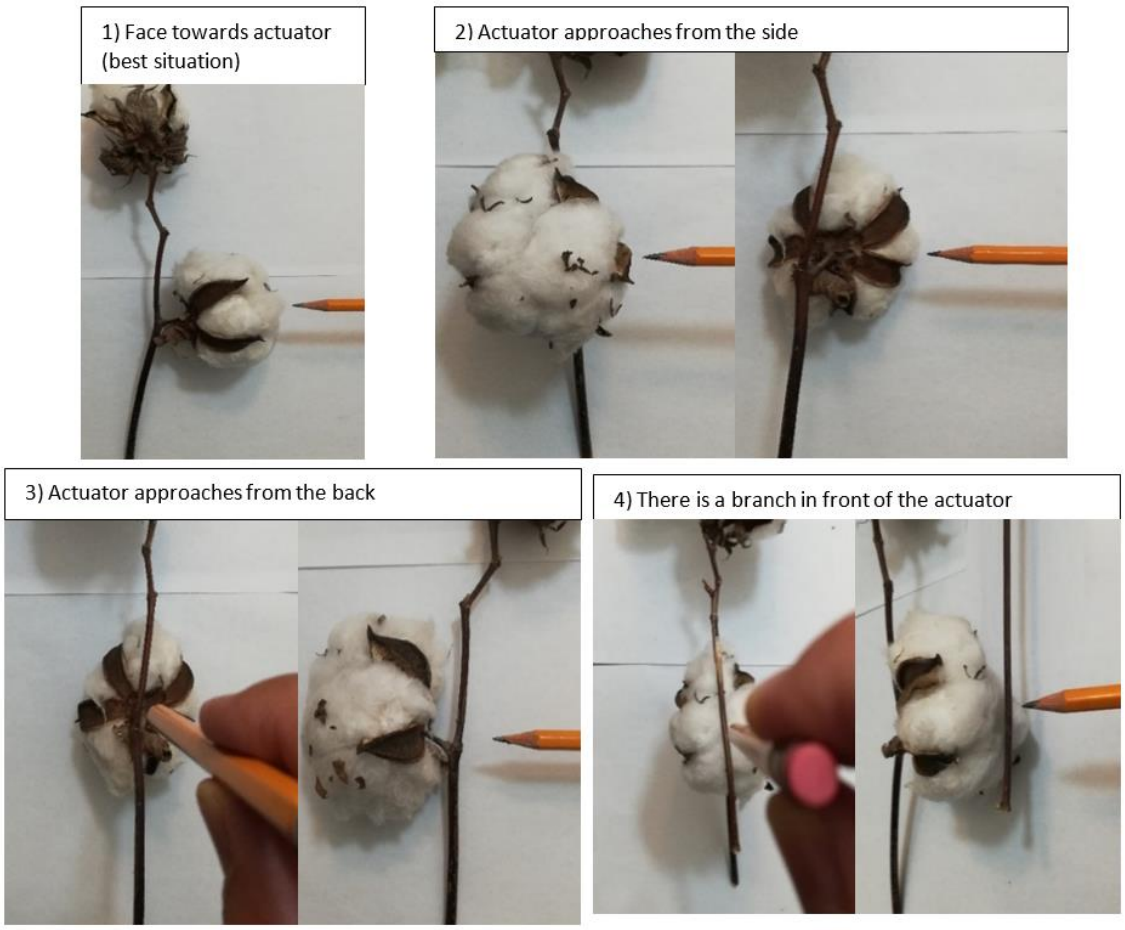

Figure 1. Different orientations and situations of a cotton boll on the plant.

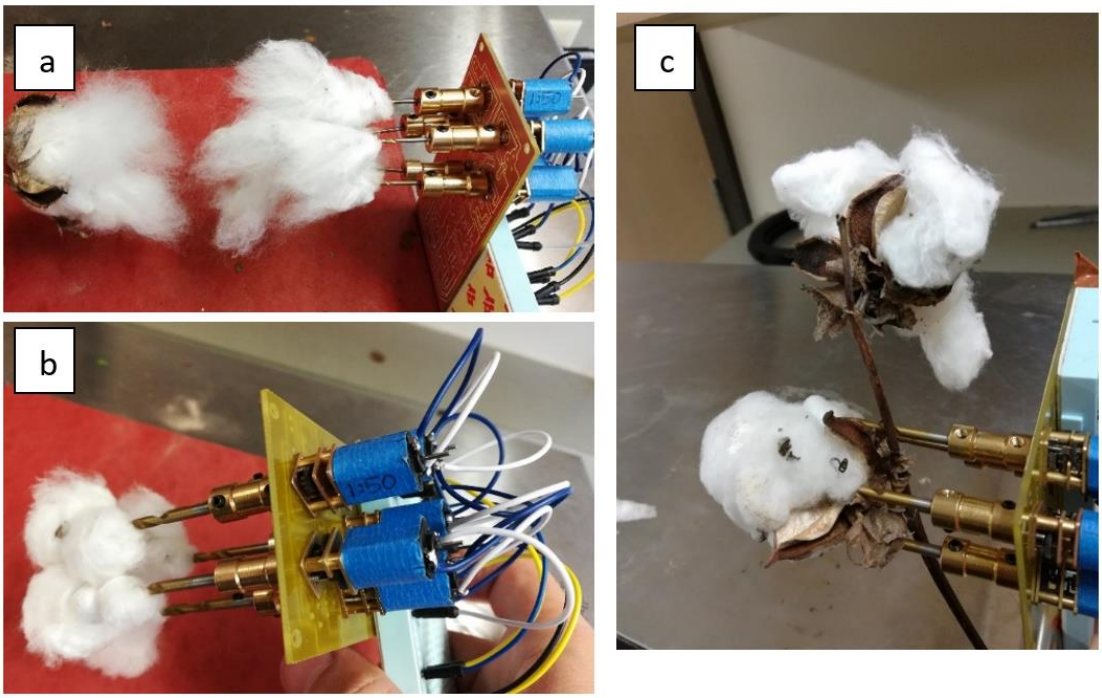

Figure 2. A five-spindle end-effector, a: seed-cotton isn't plucked completely, b: seed-cotton is wounded on two or more spindles at the same time which cased spindle bending, c: a branch got stuck among spindles.

A subsequent preliminary design has two-directional moving teeth (Figure 3) and could pick cotton bolls facing either the tip or side. The picked seed-cotton would be transferred through the fingers and would be doffed at the endpoint of the fingers.

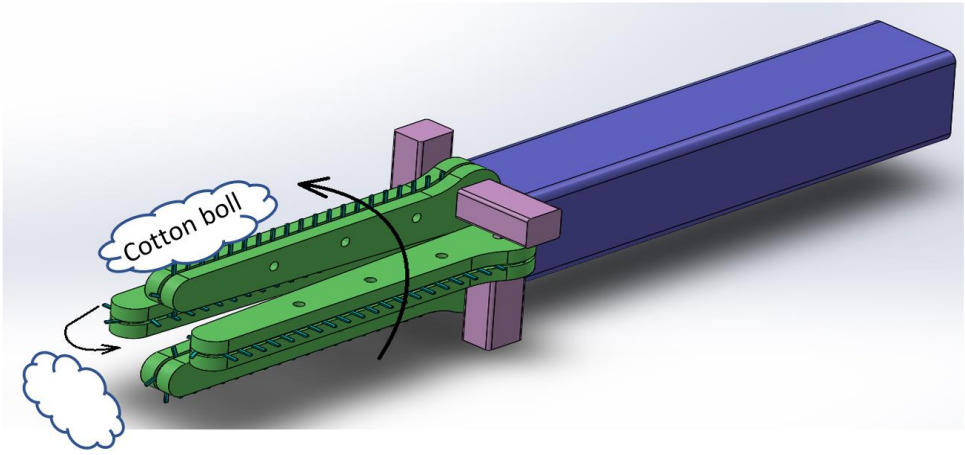

Figure 3. A computer aided design model of the end-effector which has two-directional moving teeth.

Machine Vision System for Boll Harvest and Weed Control (University of Georgia)

Cotton Boll Harvesting

Over the last two years, a machine vision system was developed that includes a stereoscopic camera, machine vision processing, a deep learning network model (YOLOv3) and an embedded computer to manage computation of the images. A red rover was used as the platform for testing the system as illustrated in Figure 4. Results have shown that bolls were identified and located with a high level of confidence using one camera looking downward when with sparse foliage later in the season.

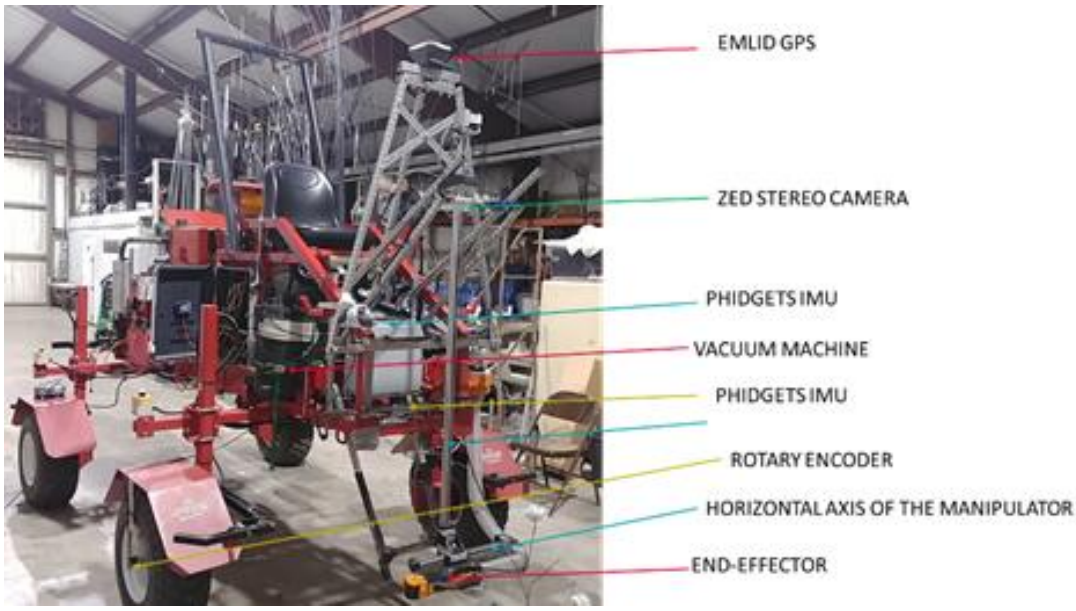

Figure 4. Red Rover platform for testing cotton harvesting system.

Cotton boll images used for training the YOLOv3 deep neural network (DNN) model were augmented 27 times using CLoDSA. CLoDSA an open-source image augmentation library for object classification, localization, detection, semantic segmentation, and instance segmentation (https://github.com/joheras/CLoDSA). A total of 2085 images were collected and labeled, and images were augmented to provide a new labeled dataset of 56,295 images.
The YOLOv3 model was used to train the dataset using Lambda Server (Intel Core i9-9960X (16 Cores, 3.10 GHz) with two GPUs RTX 2080 Ti Blowers with NVLink and Memory of 128 GB, Lambda Computers, San Francisco, CA 94107). One thousand iterations provided the optimal performance for YOLOv3, and the training took only 4 hours.

One of the main advancements made in 2019 was the development and testing of the navigation of the rover. A modified path-following technique was instituted based on the geometry of the rover. Detailed equations for calculating path curvature were found in Fue et al. (2020). The navigation system consisted of embedded computer (NVIDIA Xavier) and a rover navigation controller. The rover used two algorithms to control navigation; modified pure pursuit and PID control. The system used a predefined path of the RTK-GPS signal to navigate over the rows.

The path was obtained by recording the rover path as it drove through the cotton rows. The predefined path was then used by the rover to navigate while harvesting.

Since the rover used 5 sensors (two IMUs, two encoders, and RTK-GPS) to navigate (Figure 5), the Extended Kalman Filter was implemented for simultaneous localization and navigation. It was achieved by using the open-source library "Robot localization," which provided sensor fusion and nonlinear state estimation for IMUs, encoders and GPS. "Robot Localization" was implemented in ROS (Robot Operating System) which was robotics middleware used for robot software development. The IMUs publish two ROS topics (imu_link1/data and imu_link2/data), encoders publish wheel odometry (/wheel_odom) and RTK-GPS publish /gps/fix signal. The EKF localization used the nav_sat_transform library to integrate fix data from the RTK-GPS. Basically, "navsat_transform_node" required three sources of information: the robot's current pose estimate in its world frame, an earth-referenced heading, and a geographic coordinate expressed as a latitude/longitude pair (with optional altitude) (http://docs.ros.org/).

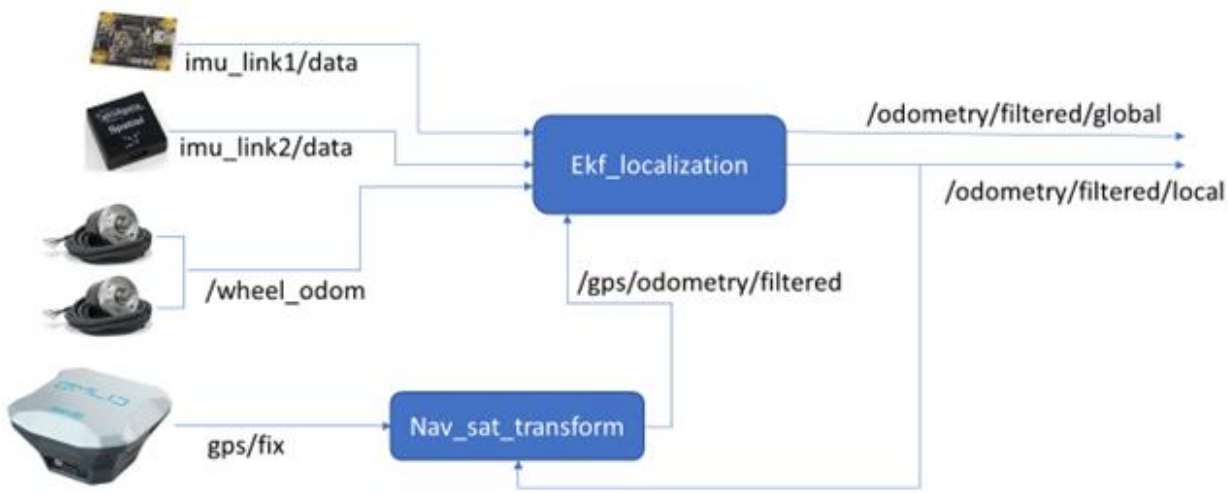

Figure 5. Simultaneous localization and navigation of red rover using a dual extended kalman filter.

Initial testing was conducted on a grassy field in Tifton, GA. This rover achieved pure pursuit tracking by following six steps; determine the current location of the rover, find the path point closest to the rover, find the goal location, transform the goal location to rover coordinates, calculate the curvature and request the rover to set the steering to that curvature and then update the vehicle's position. The rover had an absolute mean error of 0.189 m, median of 0.172 m, a standard deviation of 0.137 m and a maximum error of 0.986 m. Most of the path error occurred during turning when it was more challenging to maintain absolute path tracking.

Boll picking used the combination of navigation and boll localization to control the x-y position of the cartesian arm with end-effector. Initial testing was performed on a grassy field using cotton stalks in 12.5cm dia, pots. Three bolls were randomly placed on cotton stems in a row of 6 pots for a total of 18 bolls to harvest. Fue et al. (2019) provided a detailed table of results. Running the rover over the bolls for six repetitions, with boll arrangements changed for each test

resulted in all bolls being detected and located, a mean of 16 bolls being successfully picked with an average cycle time of 17.3 seconds per boll.

A test in the field was conducted two times in November and December, respectively. In each of these tests, bolls were picked as found in the field without cotton plant defoliation; however, the field tests were late in the season when foliage was sparse and not representative of early season harvesting. In each test, approximately 5.3m of row was picked. Results showed that for the first test, the robot picked 67 and left behind 17 bolls, which means the Action Success Ratio (ASR) was 80%. The rover was able to reach (Manipulator Reaching ratio (MRR)) 94% of the bolls (79 bolls). For the second test, the robot picked 89 and left behind 26 bolls which means the ASR was 77%. The rover was able to reach MRR 96% of the bolls. The average ASR was 78.5%. the average MRR was 95%.

Weed Detection

The weed detection and control system focused on machine vision to classify weeds in images collected while moving through the field. The actual operation of the system would include a diode laser, herbicide spot-spraying nozzle and mechanical weeder to control weeds when in the seedling stage. Knowing which weed needs controlling will allow for the selection of the best control method. For example, weeds in the row with cotton can be controlled using the laser. Weeds that are between rows and known to have herbicide resistance could be controlled with laser or mechanical weeder. Control can also be rotated between tactics to help reduce resistance to a specific control method.

Training images of 12 weed species were collected: crowfoot grass, goosegrass, crabgrass, Texas panicum, yellow and purple nutsedge, pigweed, pitted morningglory, ivyleaf morningglory, smallflower morningglory, and sickelpod. Due to the large parameter space of the deep convolutional neural networks, it requires many labelled samples for training to give a more accurate inference. Gathering enough sample images is and annotation (labeling) each images to indicate their corresponding class was very labor intensive and costly. One way to get more labelled data is to use the existing images and corresponding labels, augmenting them while maintaining the labels of the objects in the images. CLoDSA was used, as with the cotton boll data, to augment labeled data to significantly increase the labelled images database. Using this technique, 21,114 augmented labelled images from 782 original labelled images (7 classes of weed) were obtained, which significantly improved machine training.

Using the labeled images, three DNN models were tested to identify weeds (YOLOv3, SSD, Faster -RCNN). Current experiments with YOLOv3 using the 21,114 images are being used to train and validate the model to classify and detect seven (7) classes of the 13 weed species; pigweed, and the grass types (crowfoot grass, goosegrass, crabgrass, Texas panicum, yellow and purple nutsedge). The model has been able to detect the images that are currently in the database with 86% accuracy using the Yolov3 model.

ClearPath Platform for Harvest and Weed Control (Clemson)

Commercial small Unmanned Ground Vehicles (UGV) or mobile ground robots with navigation sensing modality provides a platform to increase farm management efficiency. The platform (Husky from Clearpath Robotics) can be retrofitted with different manifolds that performs

specific task, e.g. spraying, scouting (having multiple sensors), phenotyping, weeding, harvesting, etc. An autonomous map-based robot navigation (shown in Figure 6) was developed and a selective harvesting proof of concept was also designed and field tested in 2018. The robot was retrofitted with a vacuum-type system with a small storage bin.

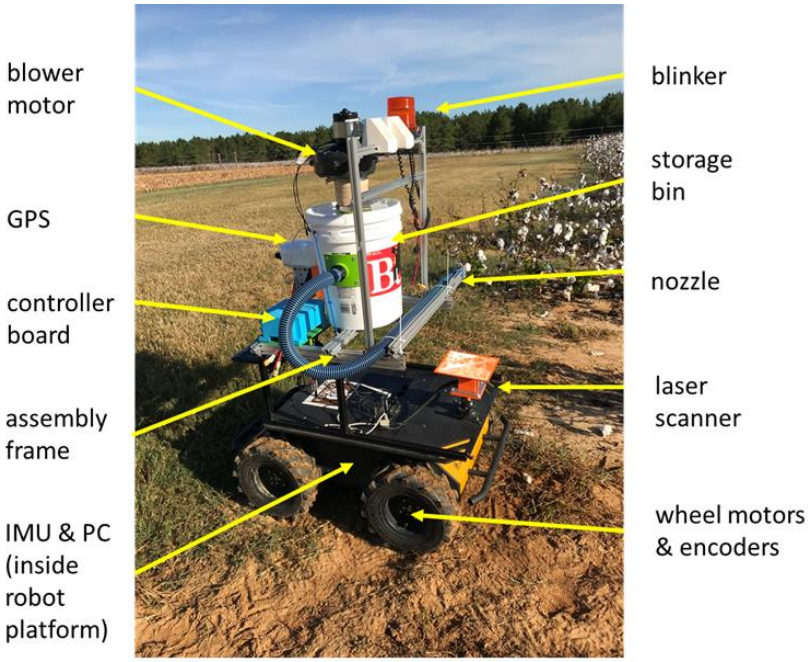

Figure 6. Mobile Robot Platform with a harvester module prototype for cotton.

Performance evaluation for the cotton harvesting was performed in terms of how effective the harvester removed the cotton bolls and the effective distance (Burce et al., 2019).

Using the same robotic platform, a new weeding module was designed and tested in 2019 that can be used for precision weed control, broadcast insecticide, and fungicide applications. Two weeding mechanism were proposed for 2019; a mechanical weeder prototype, and a sprayer prototype which will be mounted or attached to the mobile robot. Only the mechanical weeding module is discussed in this paper. Figure 7 shows the chassis and hitch model of a mechanical motorized weeding module. The design was based on a commercial automatic tiller. Due to the issue of power and motor requirements, a new design was developed to simplify the mechanical module without the use of motor and instead use simple multiple spokes to break up the soil. Figure 8 shows the mechanical weeding with the same chassis and hitch model. Figure 9 shows the prototype of the weeder module during the field test on the speed of the mobile robot platform. The field test results showed that the terrain had no significant impact on the mobile robot platform movement. Although, additional weight on the weeder is required to improve movement of the weeder module.

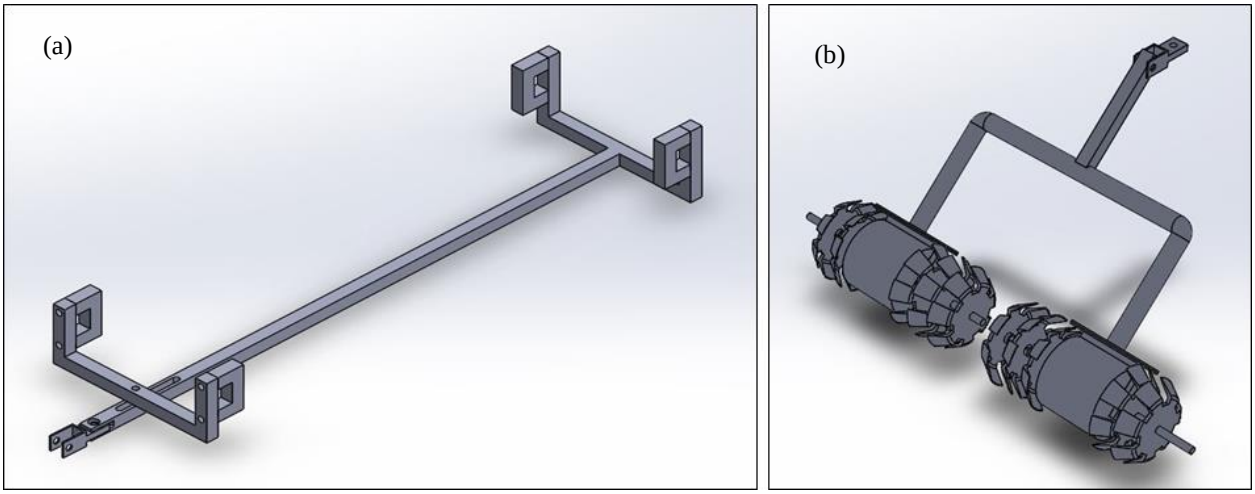

Figure 7. (a) Chassis and hitch model and (b) motorized weeding module

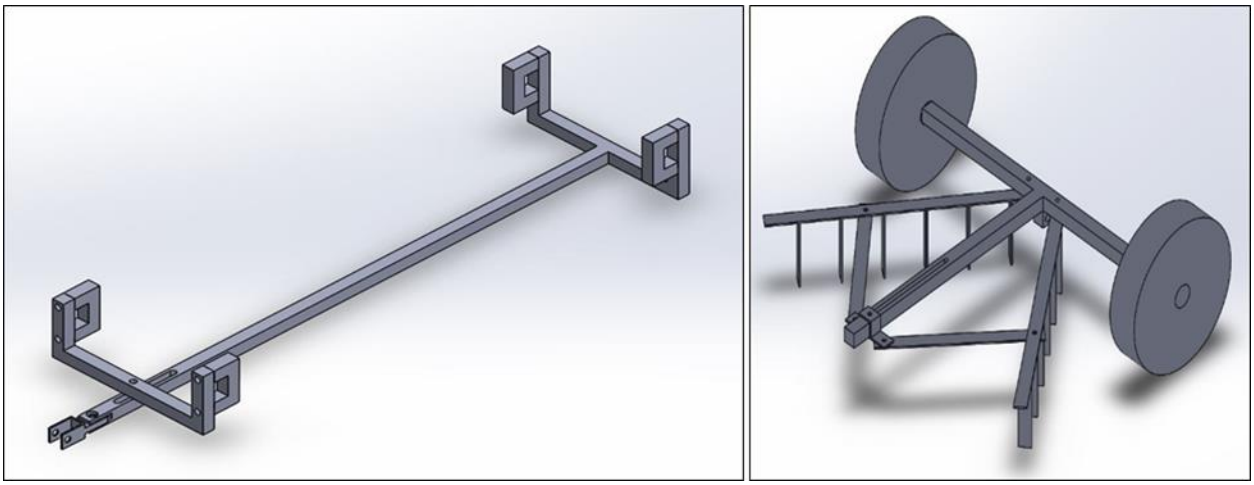

Figure 8. Chassis Model and Mechanical Weeding Module.

Figure 9. Photos of the weeder module during field tests.

Conceptual Approaches for a Robotic Harvest System

All of the work to date has been accomplished in less than two years and there is still significant work to be done before a practical prototype harvester is tested. One conceptual design is picture in Figure 10.

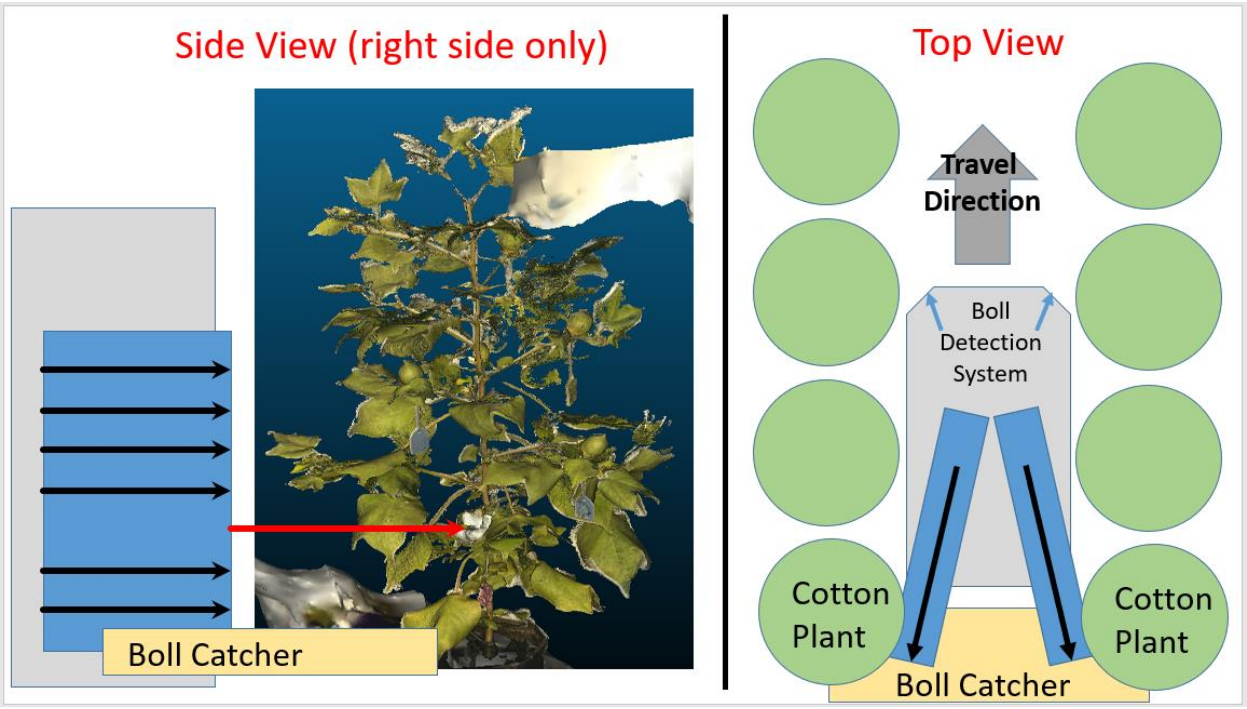

Figure 10. Conceptual robotic cotton harvest system (cotton plant representation complements of the USDA-ARS, Maricopa, AZ).

The black arrows represent a retractable array of "arms" that can be extended when a cotton boll is detected at that height on the plant. The end of each arm could contain a device such as the one previously discussed in Figure 3. The red arrow represents an arm that has been extended to harvest a cotton boll (side view). This only requires one degree of freedom of control when machine speed is accounted for and should allow a desired harvest rate of four bolls per second. Looking from the top view, the array of arms are set up to harvest plants on both sides of the machine and are at an oblique angle to the row to allow them to be longer than if perpendicular to the machine (minimizes machine width to fit between the rows). A system with a forward-looking detection system allows more processing time before spindle needs to be triggered and also allows multiple view angles of the plant so bolls behind leaves or stems can be detected. The doffing action occurs when spear is retracted into housing – the boll dislodged and falls to bottom of unit (boll catcher). The boll catcher could then mechanically conveyed seed cotton to a small trailer behind the unit. The trailer would then empty to a "boll buggy" robot at the end of the row that could then deposit the seed cotton into a stationary round module builder at the end of the field. This assumes a small independent harvester similar to the Clemson ClearPath unit (Figure 6). Alternatively, the system in Figure 10 could be treated as a row unit and several units mounted on a system similar to the UGA Red Rover platform (Figure 4). With a high clearance platform, the system should still be capable of multi-harvest without significant plant damage.

This is only one concept under consideration. Another example is one where there is non-selective harvest of a limited part of the plant (for example, bottom 5 nodes in the first harvest cycle) at a high rate of speed (no boll detection). A slower "gleaner" robot then follows using a machine vision system to collect any bolls that were not captured. Additional concepts are under development and the economic models described in a following section will be an important component in ranking various concepts.

Frequent Harvest Studies (Texas A&M, University of Georgia, University of Tennessee)

In 2018 and 2019, much of the Cotton Belt received above average rainfall during the harvest season causing harvest delay. Cotton acres have increased across the cotton belt the past three years. This acre increase causes an amplified strain on harvest equipment leading to more scheduling complications, mechanical failures, and decrease in crop removal time. Even with the most efficient harvesters operating in the timeliest manner, lower positioned mature cotton bolls are left exposed to weathering for over 50 days while the upper position bolls are maturing and waiting to open. This is particularly important in the areas of the US where tropical storms that commonly occur in the fall can drastically limit lint yield. In traditional production systems, cotton harvest aids are routinely applied when 60-80% of cotton bolls are open and then harvested approximately 1-2 weeks later in the best of scenarios. Robotic harvesting would allow for a timely seed cotton harvest as the bolls open, preserving yield, fiber and seed quality, and ultimately improving profitability. Multiple timing harvesting events will also allow for a greater uniformity of cotton fiber quality characteristics and fiber grades from each harvest event (Kothari et al., 2015). This fiber uniformity should provide additional market opportunities and premiums for farmers.

To better quantify the potential value of frequent harvest to calibrate the economic models, frequent hand harvest studies (goal to harvest two times per week after first open boll) was conducted at two sites in Texas (irrigated site near College Station and a non-irrigated location near Vernon), and one near Tifton, Georgia in 2018 and 2019 and also in west Tennessee in 2019. A similar experimental protocol was followed at all four sites. The primary treatments were: 1) frequent harvesting by hand throughout the season (no defoliants applied); 2) hand harvesting one time at the end of the season; and 3) machine harvesting one time at the end of the season following accepted defoliation practices. All sites except for Georgia conducted the harvest treatments across two varieties. Measurement of the fiber quality (HVI and AFIS) from the 2019 study are not complete at the time this paper was submitted and data analysis is still in process. Some preliminary results from Georgia and the College Station Texas locations follow.

Georgia

In 2018, the multi-harvest approach required 10 pickings from the beginning of the hand-harvest period to the end (Figure 11A). In 2019, there were also 10 pickings, with two of them occurring after the one-time harvests had been conducted (Figure 11B). There would have been more pickings for the multi-harvest approach except that the first harvest was delayed due to rainfall in 2019, causing a larger portion of the total yield to be accounted for in the first harvest. Multiple hand harvests provided a significant yield benefit over both single harvest approaches (one-time hand picking and one time machine picking) in 2018 (Figure 12A). This is likely due to

hurricane Michael, which came through before the crop had been defoliated but after a significant number of bolls had already opened. In 2019, there was a substantial amount of rainfall for the earliest harvest dates, but no significant weather events that would have caused an appreciable loss of seed cotton. In 2019, there was also a significantly higher yield for the multi-harvest approach when compared with the one-time machine harvest method. However, in this season, the one-time hand-picking also out-yielded the machine harvest, which was somewhat unexpected given the results of 2018 (Figure 12B). Nonetheless, these results indicate that the ability to identify and pick every open boll in a timely manner has substantial potential to improve yield in or production environment.

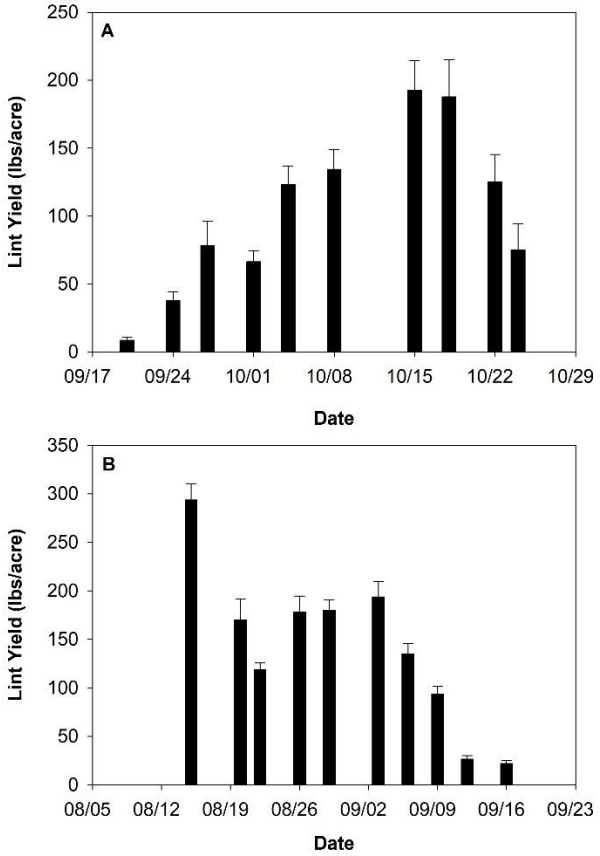

Figure 11. Lint yield for multiple, sequential harvest dates during the 2018 (A) and 2019 (B) growing seasons near Tifton, GA. Values are means ± standard error (n = 12).

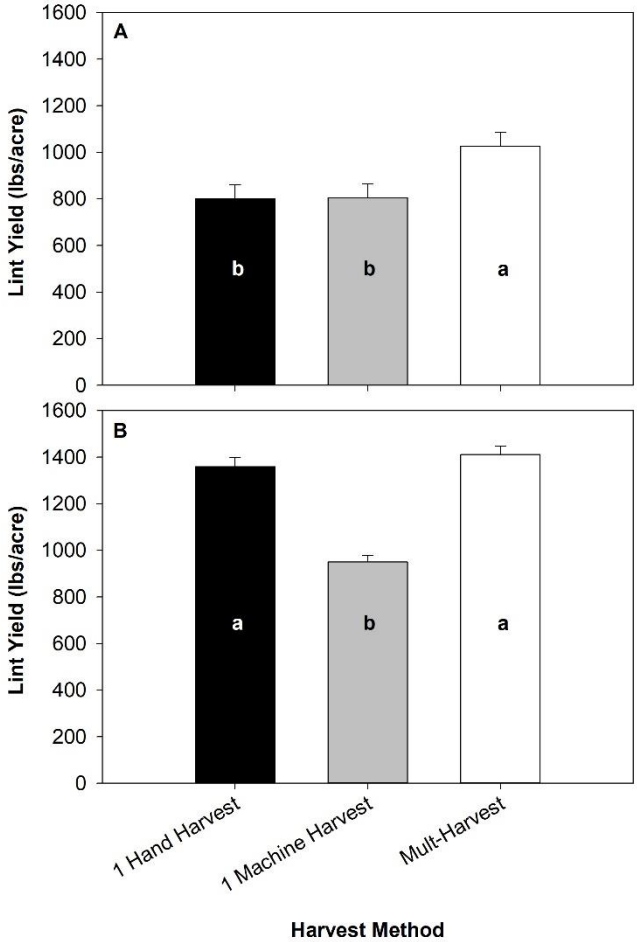

Figure 12. Lint yield for three different harvest methods during the 2018 (A) and 2019 (B) growing seasons near Tifton, GA. Values are means ± standard error (n = 12).

College Station, Texas

Two cotton varieties with different maturities, DeltaPine 1612B2XF and 1646B2XF, were planted in a randomized complete block design with 5 replicates at the College Station site. In 2018, no statistically significant yield differences between harvest methods were observed, although DP1646 B2XF statistically yielded higher by 136 pounds of lint per acre. First position bolls represented fifty two percent, second position twenty five percent, third position and vegetative bolls twenty three percent of the total weight that were hand harvested averaged across varieties. Cotton fiber quality from the machine harvested method produced inferior grades compared to the two meters of row, which were harvested merely a day apart. Both of the single harvest methods produced lower fiber grades than the multi picking method. This occurred mostly due to higher color grades from the nine inches of accumulated rainfall during month of September for our location. The machine harvest method was approximately ten cents and five cents per lint pound lower than the multiple handpicked and two meters of row harvest method, respectively.

In 2019, HVI measured trash percentage area, leaf count, reflectance, and yellowness were all significantly worse grading than any of the multiple hand harvest events. Figure 13 provides an example of how HVI measured reflectance varied by harvest event. Total lint value, including premiums and discounts will be calculated and total value per acre will be determined in the near future. Rainfall events and fiber harvested on higher nodes and vegetative branches reduce fiber quality as the harvest season progressed. Color and leaf grades resulted in the largest differences when comparing the machine harvest and multi-handpicked methods, with the latter being better grading and more consistency. Micronaire, uniformity, strength, and length consistently decreased as later hand picking events. Although some of this correlation can be attributed to harvesting higher positions on the plant that often produced lower lint grades (Bradow and Bauer, 1997; Kothari et al., 2017). Higher on the cotton plant fruiting positions do not receive the same allocated resources (Bauer et al., 2000) and often go through harsher developmental weather conditions, namely heat in south Texas (Davidonis et al., 2004). Further research and data analysis needs to occur in order to accurately determine if weather events or boll disbursement have a greater effect on fiber quality from the later hand harvest timings.

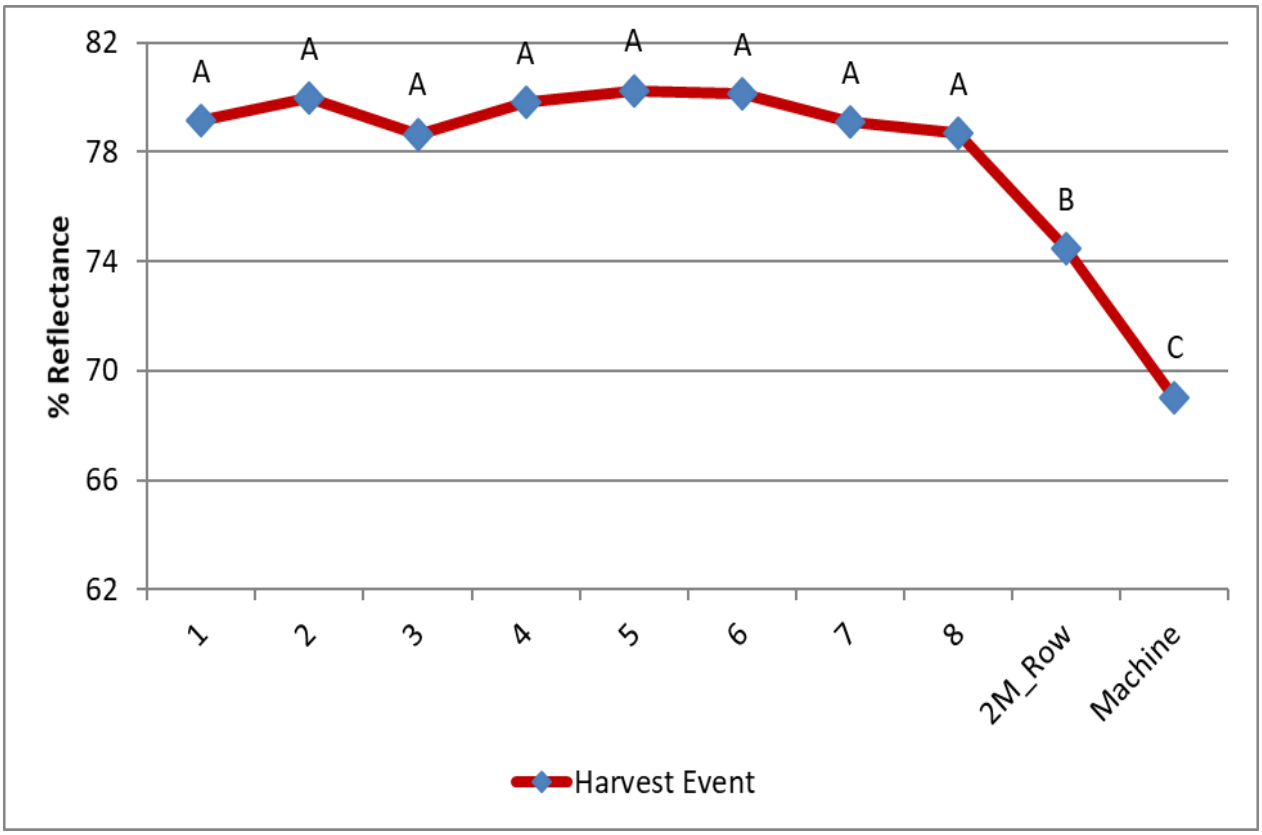

Figure 13. 2019 Reflectance percentage from HVI for each harvest timing and method at the College Station, TX.

Cumulative percentage of lint weight for each harvest date and positions in 2019 are noted in Figure 14. First position bolls represented fifty two percent, second position twenty five percent, third position and vegetative bolls twenty three percent of the total weight that were hand harvested averaged across varieties. When combining the yield data from 2018 and 2019, there were no statistically significant lint yield differences between harvest methods were observed

from the two combine site-years, although the cumulative multiple-harvest method had 190 lbs/a of lint (Figure 15).

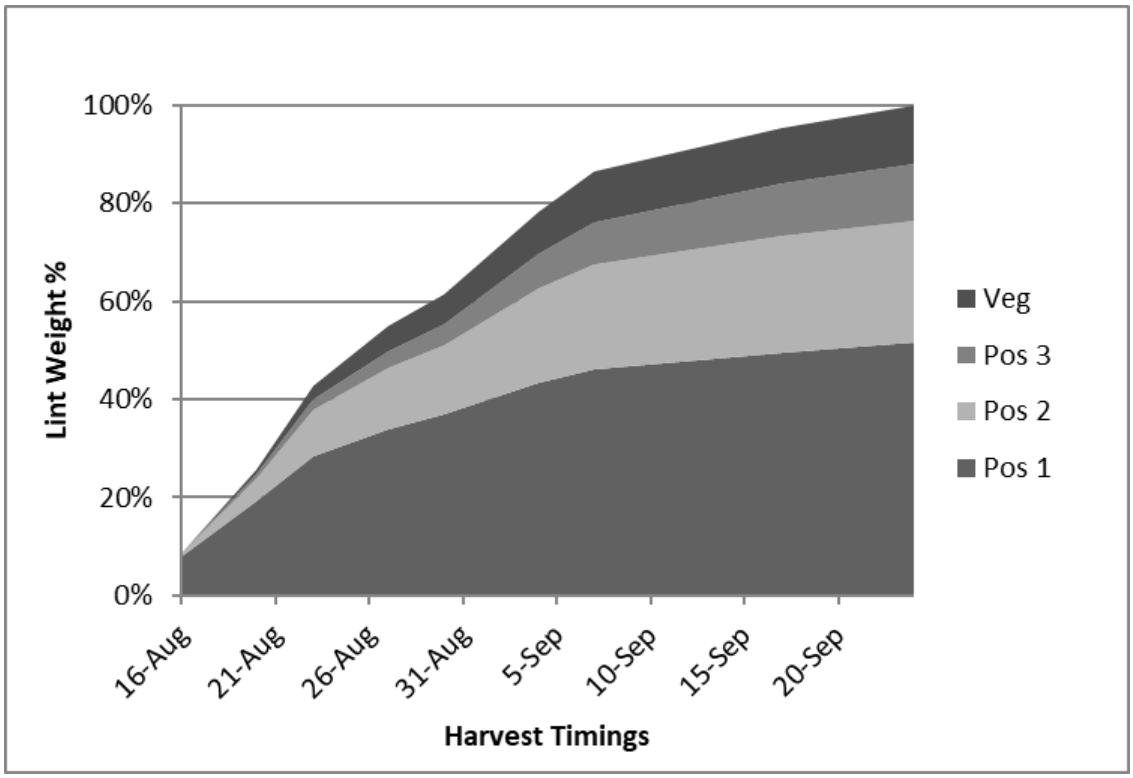

Figure 14. 2019 Cumulative Percentage of lint weight for each harvest and for each position at College Station, TX.

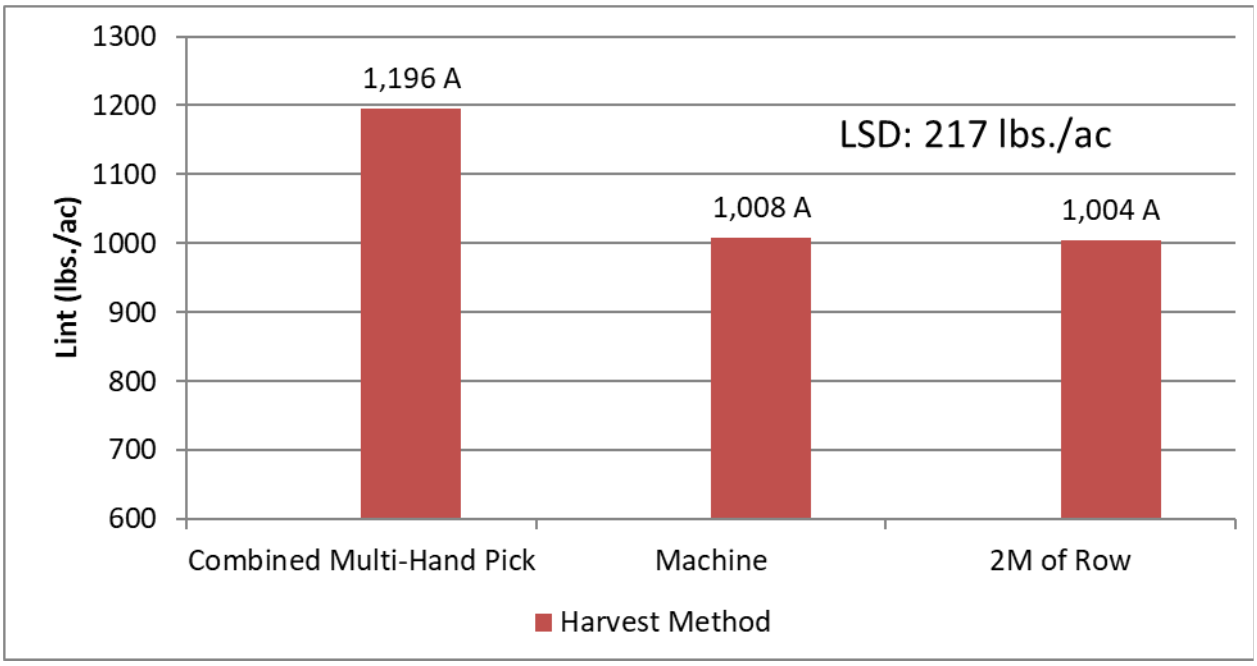

Figure 15. Combined lint yields for 2018 and 2019 for each harvest method in College Station, TX.

Initial data from the west Texas and Tennessee sites indicated a small impact of harvest method on lint yield. It is clear the weather conditions after first open boll will be the most important factor in determining if there is any yield advantage to frequent harvest.

Economic Model Description (KSU)

Two distinct methodologies were applied to support economic analysis. One was based on potential capacity with a financial analysis. The second incorporated stochastic nature of weather and yield probabilities rather than relying upon deterministic metrics. Both perspectives have been developed into interactive dashboards such that interested individuals can enter farm-specific parameters.

Evaluation of the number of robots needed to replace the status quo systems relies upon a range of machinery and environmental parameters. Many of these attributes are farm-specific such that a single use-case would not be sufficient to provide global recommendations across cotton producing areas; therefore, interactive dashboards were created so that the end-user could not only enter their own parameters but change those parameters for a series of their own sensitivity analyses.

The deterministic capacity calculator is currently available on the development site at:
https://agmanager.shinyapps.io/cottonHarvestEconomics/

The dynamic analysis dashboard is available at:
https://exchange.iseesystems.com/public/gregibendahl/ibendahl/index.html#page1

The deterministic model dashboard allows the user to select their chosen state to populate the calculator with data specific to their state from USDA-NASS. Days suitable for fieldwork and crop progress for planting, percent open bolls, and harvest are collected and presented for exploratory analysis on the first tab. The third tab allows the user to select the time window for two separate harvest systems (such as basket versus modulating picker, or modulating picker versus autonomous robotics). In addition to the harvest window that populates calculator with number of days to harvest given long term probabilities, the user can select machinery parameters such as field efficiency, ground speed, swath width, hours worked per day, days worked per week, etc. for each system. The user can also select the number of machinery units for either harvest system; this is specifically useful for comparing a single cotton picker, i.e. status quo, to swarms of modular robotics. Interactive graphs allow the user to change any of the before mentioned parameters to receive visual assessment of the probabilistic number of acres potentially harvested. This partially answers the question of “how many small bots needed to replace status quo such that harvest is completed on same date”. Parameterizing a whole-farm linear programming model using capacity metrics from the comparison above, returns to fixed costs for a series of scenarios can be calculated and then compared to a base scenario farm.

Opportunities for Robotic Systems and Automation in Cotton Production

There are many examples of robotic and automated systems currently in use by different agricultural production systems. Open source tools for agricultural application of the Robotic Operating System (ROS) has been formed and several open source tools are now available (http://rosagriculture.org/). The following sections of this paper review automated and robotics systems used in other crops that could be applied to cotton production and ginning as well as identify new applications that are potentially needed for cotton in addition to the work summarized in the previous section.

Preplant Operations

Soil Sampling

A company in Canada, Robo Ag (https://www.rogoag.com/), has adapted a Bobcat T450 platform to collect soil samples autonomously. The system is able to cover 80 acres an hour when sampling a 2.5-acre grid. A high-speed auger is used to collect sample and automatically bags the soil and store up to 250 samples on board. Currently the company is using the automated system as part of their soil sample service and are not selling individual units to producers or consultants. Valjaots et al. (2018) report on a similar platform developed for research use and also discuss the possibility of conducting real-time soil measurements in addition to sampling. Given the current progress in this area, autonomous soil sample collection is likely to become more widespread in the next five years. As robotics become more common on farms, soil sampling will be an ideal off-season task for multi-use robots.

Planting a Cover Crop

One challenge to the use of cover crops in cotton is getting them planted early enough to produce enough biomass to suppress weeds, reduce soil erosion, and build soil carbon. There have been attempts in corn to use a small robot to seed the cover crop between the corn rows before it is harvested (https://www.farmprogress.com/precision-ag/robot-attempts-nitrogen-sidedress-cover-crop-seeding), allowing for a much earlier planting date for the cover crop. One barrier to the use of cover crops by U.S. cotton producers is the added management and labor needed near and during harvest, one of the busiest times of the season. If the process could be completely automated, including refilling seed, it would make cover crops more feasible for a greater number of producers.

During peak boll opening the robot will be tasked with cotton harvest, but either late or early in the boll opening process would provide time to plant the cover crop. Other precision application uses of robots in cover crop management could include: selective N fertilization where cover crop growth is slow, early or late chemical termination of cover crops depending on soil moisture levels, mowing of cover crops to reduce herbicide use, gap filling of cover crops, selective planting dates for cover crops to avoid excess biomass in some parts of the field, variable seeding rate and species blend planting of cover crops.

Preplant Weed Control

The ability to automatically segregate green vegetation from bare soil and crop residue is well established using red (~680 nm) and near infrared (~800 nm) spectral regions, as actively growing plants strongly absorb red light and have very high reflectance in the NIR (about 50% reflectance). One of the first commercial sensor-control herbicide application was the WeedSeeker® that used a modulated light source to detect green vegetation material and then activate a solenoid valve to turn on the spray nozzle. It was found to work successfully in cotton (Sui et al., 2008). Swarm Farm, an Australian autonomous vehicle company (https://www.swarmfarm.com), has used Weedit technology (similar to the Weedseeker, https://www.weed-it.com/) for preplant weed control on autonomous sprayers.

Planting

Cotton planting is currently done by large multirow systems to cover as much acreage as possible during narrow planting windows when soil moisture, soil temperature and forecast weather are favorable. However, the ability of small all-wheel drive robots to navigate wet fields without severe compaction or ruts may complement current planters when parts of a field are too wet for large equipment to enter. This occurs frequently around playa lakes in West Texas and on Delta clay soils where drainage is poor. Fendt has proposed a swarm robotic concept referred to as "Project Xaver" (https://www.fendt.com/int/xaver) to crop planting that may be useful for cotton in such wet field conditions.

Gap Fill Planting

The ability to image fields for delayed emergence, skippy stands, seedling desiccation or death and to combine these data with a robotic planter that is guided by a drone to focus solely on the parts of the fields with poor stands offers growers a timely tool to substantially increase a uniform healthy stand. With large planters, growers must wait multiple weeks after emergence to assess stands before considering the difficult replant decision for large sections or entire fields. With small robotic planters, growers could elect at the earliest possible time to put additional seed in the ground without removing the original plants. This decision could be made multiple times during the planting window with software that records replant seed placement and models its progress to emergence. This targeted planting could be a significant saving on seed costs, seed treatment costs, crop termination herbicides, labor, and equipment operation costs.

Uncapping after Planting

One of the successful tools for stand establishment under dry-windy, poor seedbed or saline conditions is to cap the bedded row by hipping a small (~ 4 inch tall) soil behind the planter. This can be successfully uncapped by dragging a medium weight chain anytime between 1 day after planting until 1 day before normal emergence (without a cap). The weight of the cap keeps the hypocotyl from unfurling. When the cap is removed close to a normal emergence time, emergence is observed within 1 day as the hypocotyl quickly unfurls due to the built-up turgor pressure. This method is not adopted because of the labor required to uncap at a time when labor is being used to plant and due to the risk of rain after planting that would prevent entry of tractors to uncap. Robotic uncappers solve both the labor and field access problems and could handle many acres in a day since they can enter wet fields, uncapping energy use is low and there is no need for in-row precision or seed/chemical refilling.

There may be other planting innovations that are possible with robots, that we have not considered. Growers have been moving away from applying herbicides, fungicides or starter fertilizers at planting because they deem it necessary to focus only on planting. There may be a role for robots in applying pre-emergent herbicides or other starter chemicals.

Within-Season Management

Stand Evaluation

A useful evaluation of stand health is accomplished by comparing plant growth at two time points to expected growth considering heat units. A narrow focus thermal camera could also calculate a crop water stress index (CWSI) on each plant. This could be precisely done with an imaging robot or drone with images that are precisely georeferenced. Ideally lack of growth or high CWSI would be paired with replanting capabilities allowing additional seed placement where early plant growth had stalled, suggesting root injury. A benefit of running imaging robots in the field weekly or near-continuous basis is the ability to detect nutrient deficiency or drought early enough to make a correction before significant yield loss resulted.

Another potentially valuable cotton growth evaluation tool is LIDAR scanning, which enables accurate mapping of all plant heights, widths, and branching geometry. LIDAR data can measure positions of plant stems, branches, leaves, and bolls to sub-centimeter accuracy which could be used in near real time to evaluate stands with respect to norms established for each plant variety. When combined with conventional and thermal imaging, LIDAR data could be used to locate and possibly correct problematic sections within fields.

Precise geolocation of early season plants could be the first step in managing the inputs for each individual plant. It could also be an important data layer to assist in weed control decisions later in the season by ensuring no tillage or herbicides are applied to that point in the field.

Crust Busting

Robots would be ideal at crust busting. If they had precise GPS, a variable down pressure rolling spike that also served as a soil penetrometer, ability to sense emerged cotton seedlings and both forward and reverse imaging, then they could detect skips and apply a very precise force just to the side of the drill row that only broke the crust and pushed no further. Since this kind of robot would not damage emerged cotton, it could be deployed earlier than current broadacre crust busting practices that damages some emerged plants. Since soil moisture content is critical for ease of crusting busting the back facing camera compared with the front facing camera could be used to determine if the crust was being broken and either adjust more down pressure or delay a day until the crust had dried more.

Sand Fighting

Traditional sand fighting is done after a rain when the soil surface has lost its roughness. However, robots may be useful during a rain to build surface roughness from the wet soil. There may even be utility for a robot to create roughness prior to a rain or paired with a drone to focus sand fighting where the greatest amount of sand is blowing.

Weed Control

There is substantial public and private sector activity in robotic systems for within season weed control, and Slaughter et al. (2008) provide a comprehensive review of past efforts, and several current systems are summarized by Gaines (2018). Lamm et al. (2002) reported on one of the first applications of a robotic system for within season weed control in cotton. Using a machine vision system, they were able to correctly spray 89% of weeds in the field and misapplied herbicide to cotton 21% of the time. Since then, many systems have transitioned to using machine learning for weed identification, coupled with a wide range of weed removal methods. Distinguishing weeds from crops is a challenge even for today's best machine vision systems, but several prototypes from both industry and universities are showing promise.

Multiple efforts are taking a "see and spray" approach using computer vision and machine learning to detect weeds between rows. The tractor-mounted equipment from Blue River Technology (Sunnyvale, CA, USA) utilizes a controlled lighting cover and two sets of cameras to identify and spray weeds in real-time. Although originally developed for lettuce, both the Robovator (F. Poulsen Engineering, Denmark) and the Robocrop InRow Weeder (Garford Farm Machinery Ltd., Peterborough, United Kingdom) use vision-based techniques for mechanical weed removal, and this technology could be adapted for future use in cotton.

In addition to tractor-mounted autonomous weeding implements, multiple companies are developing small, standalone autonomous robots capable of weeding. Two different companies have developed a small platform for weed control using a delta arm and machine vision. Nexus Robotics (Halifax, Nova Scotia, CA) has a small platform, the R2-Weed2, that uses a neural network to identify and either mechanically remove weeds or apply herbicide. That system is similar to a commercial prototype from ecoRobotix (Vaud, Switzerland, www.ecorobotix.com/en), which uses a Delta manipulator to apply a small amount of herbicide to weeds, and adds the use of solar panels to recharge the robot's battery while in the field. The startup Small Robot Company (Salisbury, England, UK) is developing an autonomous weeding robot that will use electricity from a system developed by RootWave (Warwick, England, UK) to kill weeds. Another non-herbicide weed removal robot is being developed by Deepfield Robotics (Bosch, Gerlingen, Germany). Their BoniRob platform uses a mechanical stamping mechanism to remove small weeds at an early growth stage.

The ability to discriminate between cotton and non-cotton combined with precise herbicide application would elevate spot spraying to a fine art. This may be the most powerful use of robots in cotton production since it would allow herbicides not currently used in season and a level of precision application not currently available. The "mode of action" from traditional weed cultivation is desiccation. With thermal imaging, it may even be possible to combine spraying and sweeping to maximize weed desiccation and kill with reduced herbicide applied.

Cotton plants that may emerge outside of the drill row are weeds because they cannot be harvested yet extract water and nutrients. Also cotton plants that emerge late in an already healthy stand are weeds. These volunteer plants could be removed with either a sweep or spot spray if detected soon after emergence.

Insect & Disease Management

The use of robotic systems to scout fields to identify problems has been demonstrated in several studies, such as Nagasaka et al.(2004) who developed a "dog" robot using a camera, laser system and CAN bus to find problems in the field. Over a large portion of the Cotton Belt fields are visited at least twice a week by a field scout to determine whether insect populations are exceeding thresholds or disease symptoms warrant a pesticide application at the cost of around $9.00/acre. As such, there is great potential to use robotic scouts to alert growers of infiltration of pests before populations exceed levels known to justify a pesticide spray. With insects, a significant challenge exists in identifying those present to species to distinguish between beneficial insects and pests as well as to distinguish between the different pests to determine which are over threshold. However, systems could be developed relying on imaging of plant damage and/or insects, pest DNA sampling, or volatile detection to determine which species are present. As an example, the ability to determine through imaging whether new leaf area is being added at a rate commensurate with heat units would add to the precision of a spray for thrips. Growers occasionally "revenge spray" thrips past the time when they are no longer an impediment to adequate leaf area expansion. Presence of thrips in the field would also need to be determined

As with herbicide applications, land- and air-based robotic systems could also be used to make insecticide and fungicide applications. Often diseases are confined to certain areas of field as are certain pests such as spider mites and would be good candidates spot spraying applications. These applications could improve pest control by penetrating deeper into the canopy given their proximity and orientation to the plant. These systems could also release semiochemicals for mating disruption, beneficial attraction or pest repellency while performing other tasks such as weed control or scouting.

Nuisance Animal Deterrent

Feral hogs, deer, rabbits, and bears are becoming another pest for cotton producers in different regions of the Cotton Belt. Hauck (2019) has patented a robot designed to autonomously deter nuisance animals. Once the animal is detected the robot is designed to simulate a predator of the target animal.

Fertility

Small swarm robots could provide the ability to monitor cotton plant foliage to identify plants or portions of the field before the onset of nutrient deficiencies or if excessive nutrients are available. The robots would be able to make real-time prescription applications, or prescription maps could be developed for use in traditional fertilizer applicators. This approach would allow growers to become less dependent on preplant fertilizer applications, which lead to more upfront expenses and increased environmental risks, especially for nitrogen.

Plant Growth Regulation

Mainstem growth rate is used to precisely time mepiquat application to reduce internode length and instigate fruiting. With robots powered by inexpensive energy there may be value in running a spraying robot through the field continuously to optimize mepiquat rates in the crop during times of excessive vegetative growth. Early applications of mepiquat can be highly effective if

low rates are applied regularly, which would lead to increased crop uniformity and optimize harvest efficiency and fiber quality. The key is to avoid PGR applications to slow growing cotton, which can cause additional stress, and robotic sensors or drone imaging could assess plant stress during multiple passes through the field, and prescriptions could be applied by swarm robots.

Mid-Season Leaf Removal

When labor was cheap in China (during the 1990's) lower leaves were hand removed once they were shaded. This was done to minimize boll rot during early boll opening. In addition, vegetative branches were also removed if the mainstem was well established. There may be utility in this practice for Target Spot, hard lock and boll rot in the humid Southeast. This method may also set up boll conditioning and a better plant architecture for robotic harvesting. Although a robotic harvester will gather early opening bolls, unless they fluff out it may be difficult for a robot to pick them. Cotton generates many more squares on vegetative branches than needed to contribute to final yield. Removal of these branches should not affect yield, assuming an adequate plant population, but will help narrow the fruiting window and reduce the need for a late-season insecticide application.

Harvest

There are currently challenges in some cotton fields located near highways and urban areas with plastic trash litering fields and ultimately harvested with the cotton. A potential near-term application for robotics systems is the use of high resolution UAV imagery to identify plastic and other contaminants present and then deploy a robot to remove those items from the field prior to harvest.

Current cotton yield monitors indirectly measure cotton mass flow based on light attenuation or microwave reflectance of seed cotton in the convey ducts and thus can require variety specific calibration factors (Vories et al., 2019). Automation of cotton yield monitor calibration has been accomplished by the use of pressure sensors to measure the weight of the basket by monitoring the static pressure in the hydraulic lift cylinder circuit of a traditional basket stripper harvester. The software running the system was split into two parts that were run on an embedded low-level micro-controller and a mobile computer located in the harvester cab. The system was field tested under commercial conditions and found to measure basket load weights within 2.5% of the reference scale (Wanjura et al., 2015 and 2016). As such, the system was proven to be capable of providing an on-board auto-correction to a yield monitor for use in multi-variety field trials. The implementation sub-systems; electronic, micro-controller firmware and human-machine-interface, HMI, software designs are provided in Pelletier et al. (2019a-c). Ongoing research is currently being conducted in a joint research effort between USDA-ARS and TAMU to extend this system to include an optical cotton yield monitor that estimates mass flow of cotton bolls in the pneumatic air ducts in cooperative research effort. Such integrated systems promise to continue the trend of "smarter" agricultural equipment in the future.

Automated identification of cotton modules is already a possibility due to Radio frequency identification (RFID) tags incorporated into the plastic wrap used to cover cylindrical cotton modules formed by John Deere harvesters. Each RFID tag contains a module identifier (module ID) that is unique to that module. Harvesters equipped with the HID Cotton Pro system from

John Deere create a database of harvest related data for each module using the module identifier as the primary key. The data files generated on the harvester can be manually downloaded onto a USB memory drive or wirelessly transmitted to a John Deere website for later retrieval. The module ID can be read from the RFID tag using electronic scanning tools and used to help growers and ginners manage modules and associated information gathered during the harvesting, storage, transportation, and ginning processes. To demonstrate the utility in this new identification system, an electronic module management system was developed that incorporates several RFID interrogation tools: 1) a mobile application for scanning modules by hand in the field or at the gin yard (Wanjura et al., 2017), 2) a system for use on module trucks that automates the process of scanning modules when loaded or unloaded (Wanjura et al, 2018), 3) a stationary bridge utility for scanning modules at the truck scale, and 4) a stationary bridge utility for scanning modules at the gin module feeder. Each time a module is scanned by one of these tools, the module ID is associated with a GPS location and client/farm/field ownership information. A data management utility was developed as part of the electronic module management system and compiles module specific information from all data sources into one location for analysis and use by producers and ginners (Wanjura et al., 2018). Two additional tools were developed that provide module and lint bale data to the electronic module management system: the Cotton Harvest File Download Utility and a PBI Logger Utility. The Cotton Harvest File Download Utility was developed by Cotton Incorporated and utilizes an API from John Deere to automatically download, unzip, and sort HID files into a file structure easily utilized by gin office staff and which can be easily imported into the data management utility. The PBI Logger Utility is a tool used in the gin to automatically scan the 1D barcode on the Permanent Bale Identification (PBI) tag affixed to each lint bale as it exits the bale press. The PBI Logger associates a timestamp and bale weight with each PBI when the tag is scanned. An algorithm titled "PBI to Round Module Mapping" was developed to automate the process of associating lint bales with the round module from which they were ginned. Associating lint bale PBI's back to the round module opens the door for fiber quality mapping at the field level once lint grade information is obtained from USDA AMS Cotton Classing Offices.

In addition to work on robotic cotton harvesting in the U.S., the use of machine vision to identify cotton bolls is underway in India (Rao, 2013) and China (Wang et al., 2008). A mechanical gripper for removal of cotton from the boll has been designed in India by Limbasiya et al. (2015). An Indian company has also developed a prototype robotic harvester that uses a vision system to identify a cotton boll and then remove it using a combination of mechanically rotating spikes and a vacuum system (http://www.grobomac.com/).

It may also be desirable to prune lower leaves and vegetative branches (suckers in viticulture lingo) once the lower bolls have been harvested. Selective application of a defoliant or boll opener during the robot harvesting to facilitate the next week's passes. In stripper harvested areas, use of robotic harvesters may allow for the avoidance of the desiccation pass, which in turn would lower production costs as well as lower environmental impact of production processes.

Ginning

As autonomous tractors and forklifts become available, the ability to automate management of cotton modules on the gin yard could not only reduce labor requirements at the gin, but also reduce human errors. Fiber bales leaving the gin could be automatically loaded in a truck or warehouse. There are already other industries making use of robotic systems for warehouse management and these systems could be adapted for cotton warehouses.

There is a growing amount of automation occurring in the ginning industry including automated strap applicators and baggers at the bale press. Systems have also been developed to automatically retrieve the classing sample, but it still requires a person to insert the barcoded tag and place in the container for the classing office. Automatic baggers to wrap finished cotton bales are also gaining adoption by U.S. gins.

Plastic contamination in cotton bales is causing a loss of market-place premium, estimated to be $0.02/kg, a loss of $500 million in annual revenue to producers. In response to this Cotton Incorporated funded projects have resulted in the development of an automated plastic removal system (Pelletier et al. 2020). The system relies on machine vision principals to detect plastic on the feeder apron of the gin stand. Low cost color imagers and processors provided by the cell-phone industry. Off the shelf processors and cameras were utilized in the prototypes that were augmented with custom hardware for interfacing to pneumatic air-knives that were used to eject the plastic contamination from the cotton stream.

Challenges to Overcome for Autonomous Applications

In discussions with U.S. cotton producers, potential challenges have been identified for autonomous farm applications. It is important to remember that any system designed for on farm use must be reliable and extremely durable. Almost all field operations, particularly planting, pest control and harvest, must occur within a narrow time window, and any delays due to equipment failure will be impediments to long-term adoption. It is also important to recognize there will be obstacles in the field such as large weeds, rocks, and deep ruts created by pivot tracks or tractors; therefore, robots with small diameter wheels will not be able to reach all areas of the field.

Autonomous systems must be comparable in terms of efficiency and performance. While several smaller systems may be able to cover the same acreage as a larger piece of machinery, the operational velocities and efficiencies of many autonomous robotics are limited by the speed and performance of real-time vision-based detection and actuation algorithms.

For equipment that will be unattended, vandalism and theft are concerns. Geofencing, the ability to transmit real-time images of any unauthorized personnel attempting to interact with the equipment is needed.

Field sizes vary across the country and it is common in the southeastern U.S. to have fields that range in size from 6 to 600 acres. Furthermore, farm operations have fields that are commonly spread over a wide geography, such as 20 mile or more radius, and over poorly accessible roads.

So for applications where the equipment is expected to cover large acres, logistics of transportation between fields must be carefully considered, especially if the vehicle must be transported on public roads as opposed to transported as a kit to be assembled on site.

In addition to being cost competitive with traditional systems, robotic systems need to have a short payback time, as it is anticipated that some of these technologies will change rapidly.

Another key point in considering automated systems for large area applications is that the system needs to be truly autonomous and require minimal management time. Using the cotton harvest example, while many cotton producers find the risk reduction to extreme weather events that frequent harvest with a robot could bring, there is significant concern about executing a complicated system at harvest time. The current harvest system used in the U.S. is a once over, round module building harvester that can allow one person to harvest as much as 10 acres per hour. The dependability and simplicity of this system partially explains its rather quick adoption in the U.S., Brazil, and Australia. If multiple automated machines were needed to replace this single machine, they must be just as dependable and self-sufficient as the current system in addition to being economically competitive.

Summary and Conclusions

The progress made in 2019 on the robotic harvest platforms illustrates the number of robotic tools that are readily available, such as autonomous navigation systems to support agricultural robots. Open source machine vision tools are also decreasing the time it takes to train a system to identify objects of importance, such as a cotton bolls and weeds. In less than 1.5 years the engineers at UGA were able to develop a system that could identify a boll in the field and control a tractor and 2-D arm to autonomously harvest bolls. Hardware costs for the machine vision system (camera, processor, software) were under $1000, suggesting an increase in the use of these tools in the future due to affordability. The work to establish an image library for economically important cotton weeds will enable more advanced automated weed control systems in the future. One conclusion from the harvest study illustrated that under certain weather conditions the ability to frequently harvest will increase yield and fiber quality. While developments in robotics offer a wide range of potential services to cotton growers, a central question surrounding their eventual deployment is how benefits may compare against costs of adoption. Researchers have developed a dynamic model that can incorporate assumptions spanning a range of possible robot configurations and applications. Key questions on the benefit side of the equation come from speed potential and reduced vulnerability to breakdown, especially considering harvest-related uncertainty coming from weather-driven threats to yield and quality. Key questions on the cost side arise from the number of robots envisioned and the variety of tasks that each robot can be expected to support.

In addition to the application of robotic technologies to cotton harvest and weed control, every aspect of the cotton production system could benefit from automation and or robotics. Current uses of robotics in agriculture are aimed at weed control and also automating intensive sampling and scouting tasks, such as soil sample collection and plant monitoring. Table 1 summarizes many of the operations during the cotton season that could benefit from robotic systems.

Table 1. Field and gin activities that could benefit from automation and technology and/or hardware needed for implementation.

	Enabling Technology and/or Hardware													
Field Activity	Forward camera	Back camera	Rolling spike penetrometer	Pairing with drone	Side Planter	Center Planter	Side Sweep	Center Sweep	RTK GPS	Thermal Imaging	Spot Sprayer	Side cutter	Center cutter	Picking head
Broad acre planting	x			x	x				x					
Gap filling planting	x			x	x				x	x				
Uncapping	x						x		x					
Stand Evaluation	x								x	x				
Crusting Busting	x	x	x						x					
Sand Fighting	x						x	x	x					
Spot Spraying	x						x	x	x	x	x			
Thrips Spray	x								x		x			
Early Mepiquat	x								x		x			
Weed cotton	x						x	x	x		x			
Leaf Removal	x						x		x			x		
Harvesting	x								x		x	x		x
Crop Management	x				x	x					x	x	x	

In the future, Cotton Incorporated will continue to support autonomous weed control and harvest applications for cotton and have all results made available in an open source format when possible. There will be an increased effort to create open source image libraries of cotton parts and weed species important to cotton to encourage commercial interest working in these areas to adapt their systems to cotton applications.

Acknowledgements

Several cotton producer comments informed the discussion of potential applications of autonomous technologies to cotton production. In particular, the following Cotton Incorporated Board of Directors members participated in a round table discussion on this topic in December of 2019: Andrew Burleson, North Carolina; Steven Clay; Oklahoma; Jerry Davis, Florida; Jacob Gerik, Texas; Shane Isbell, Alabama; Preston Jimmerson, Georgia; Nathan Reed, Arkansas; Bob Walker, Tennessee; and Mark Wright, Texas. All the grower insights have been extremely important and are greatly appreciated.

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