OPPORTUNITIES FOR ROBOTIC SYSTEMS AND AUTOMATION IN COTTON PRODUCTION

Edward M. Barnes
Gaylon Morgan
Kater Hake
Jon Devine
Ryan Kurtz
Cotton Incorporated
Cary, NC
Terry W Griffin
Gregory Ibendahl
Ajay Sharda
Kansas State University
Manhattan, KS
Glen C. Rains
John Snider
University of Georgia
Tifton, GA
Brian G. Ayre
University of North Texas
Denton, TX
Joe Mari Maja
Clemson University
Blackville, SC
J. Alex Thomasson
Yuzhen Lu
Hussein Gharakhani
Mississippi State University
Starkville, MS
James A. Griffin
Robert Hardin
Emi Kimura
Texas A&M University
College Station, TX
Tyson Raper
University of Tennessee
Jackson, TN
Sierra Young
Kadeghe Goodluck Fue
NC State University
Raleigh, NC
Mathew G. Pelletier
John Wanjura
Greg Holt
USDA, ARS
Lubbock, TX

Abstract

Automation continues to play a greater role in agricultural production with commercial systems now available for machine vision identification of weeds and other pest, completely autonomous weed control, and robotic harvesters for fruits and vegetables. The growing availability of autonomous machines in agriculture indicates there are opportunities to increase automation in cotton production. This paper considers how current and future advances in automation has, could or will impact cotton production practices. The sections are organized to follow the cotton production process from land preparation to planting to within season management through harvest and ginning. For each step, current and potential opportunities to automate processes are discussed. Specific examples include advances in automated weed control and progress made in the use of robotic systems for cotton harvest.

Introduction

Advances in machine vision, computer processing, and controllers have led to an increase in 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). 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: http://seedotrun.com/index.php). Additional evidence of the proliferation of robotics systems for agriculture is the number of Robotic Operating System (ROS) open-source tools are now available (http://rosagriculture.org/). A recent review paper that highlights challenges and opportunities for agricultural in general is provided by Pitla et al. (2020). The following sections of this paper follow the cotton production process from pre-planting to harvest and ginning discussion areas where there is potential for automation; automation applications in other crops that could be adapted; or where automated systems are in use. This paper is an update of last year's presentation and incudes many of the same comments with regards to opportunities during the season as reported by Barnes et al. (2020). The overall objective of this paper is to inform both the research community and those providing automated services for agriculture of the opportunities for current and future application of machine vision and automated systems in the cotton production process.

Preplant and Planting Operations

Soil Sampling

Daystar et al. (2017) reported that 80% of U.S. cotton producers perform soil sampling to determine fertilizer rates. 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 samples and automatically bags the soil and stores 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

The American Cotton Producers of the National Cotton Council have set 2025 goals to increase soil carbon and decrease soil erosion. A key tactic to meet those goals is the increased use of winter cover crops (NCC, 2018). One challenge to the use of cover crops in cotton is planting the cover crop early enough so that it produces 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. Another barrier to the increased 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 the robot would have time to plant the cover crop either late or early in the boll opening process. 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, Jackson et al., 1981) 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.

Mwitta and Rains (2021) have been testing similar approaches in cotton. 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 will 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.

To enable Mwitta and Rains' (2021) system for cotton, 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 were collected. Additional work is being conducted by researchers at North Carolina State University and Mississippi State University to increase the number of images available through an open source image database of weeds important to cotton. Similar databases have been developed for other crops and environments as described by Lu and Young (2020). USDA-ARS engineers are also working to develop a simulated three dimensional cotton field that can be used to adjust lighting and background conditions for training of machine vision systems. Maja et al. (2021) have evaluated the use of the ClearPath Husky robot as a platform to tow tillage implements that do not require weed detection capabilities. Two weeder/tiller prototypes were tested in 2019 and 2020. The first module has six individual prongs on each side, where each prong measured approximately 15 cm. The prong was designed to penetrate about 3.8 cm into the soil. Two wheels were used to ensure the prongs would be kept at a constant depth into the ground. A slider mechanism was designed to make the width of the two-prong holder adjustable. The second weeder/tiller was an adjustable harrow disk, where the disk holder can be adjusted at a certain angle. Since the disk used was off the shelf and heavy, it was retrofitted with two wheels to minimize the mobile robot's force to pull the weeder.

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

Plastic Trash Removal

There are currently challenges in some cotton fields located near highways and urban areas with plastic trash littering 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.

Automated Yield Monitor Calibration

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 Traceability and Tracking

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.

Frequent Harvest System

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 first cotton boll on a plant will be mature and ready for removal on average 50 days before the field is harvested under the current mechanical harvester system. The ability to frequently harvest the plant (5 to 10 times during the season) will reduce the risk of fiber damage and/or yield reduction due to extreme weather events. It will also limit the time white fly or aphids secretions result in what is referred to as "sticky cotton". Finally, as the bolls harvested during the season will have developed under similar environmental conditions, the uniformity of fiber properties such as micronaire and length is likely to increase.

End Effector for Cotton Harvest

A key requirement of a robotic cotton harvester is an appropriate end effector. Gharakhani and Thomasson (2020) conducted lab tests 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 to change its orientation; and (3) designing an end effector that can pick seed cotton without considering cotton boll orientation. A design that shows promise involves the use of rotating pins that could pull a boll into a suction device (Figure 1).

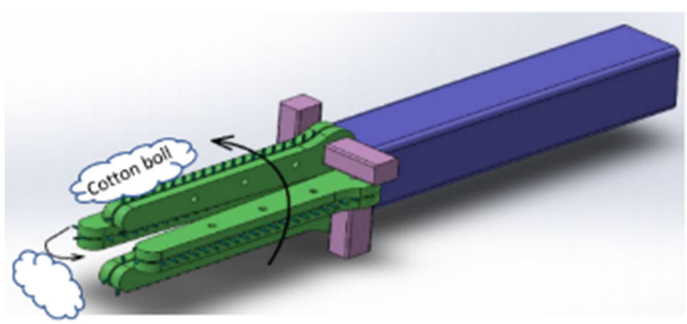

Figure 1. Preliminary design of an end-effector for cotton boll removal from Gharakhani and Thomasson (2020).

The concept for the finger end-effector is rotating pins. Multiple prototypes of this concept including one, two, and three fingers were manufactured and evaluated (Figure 2). The one-finger configuration, has the lowest picking speed, and it has difficulty transferring the seed cotton to the doffing mechanism. The three-finger configuration has the highest picking speed and the best penetration through the plant, but it tends to ingest not only the seed cotton but also the calyx and even leaves and branches. A potential solution is to move the end-effector forward and backward a few times during picking the seed cotton so that the end-effector cannot ingest undesired material. The two-finger configuration does not tend to ingest undesired material, but it is more sensitive to cotton boll orientation. Therefore, if the open cotton boll is not facing the end-effector, the end-effector must rotate until its lower surface (not the tip) is face to face with the cotton boll. In future work, the two and three-finger end-effectors will be further tested and compared by attaching them to a system of linear actuators to conduct more precise tests and optimize the system.

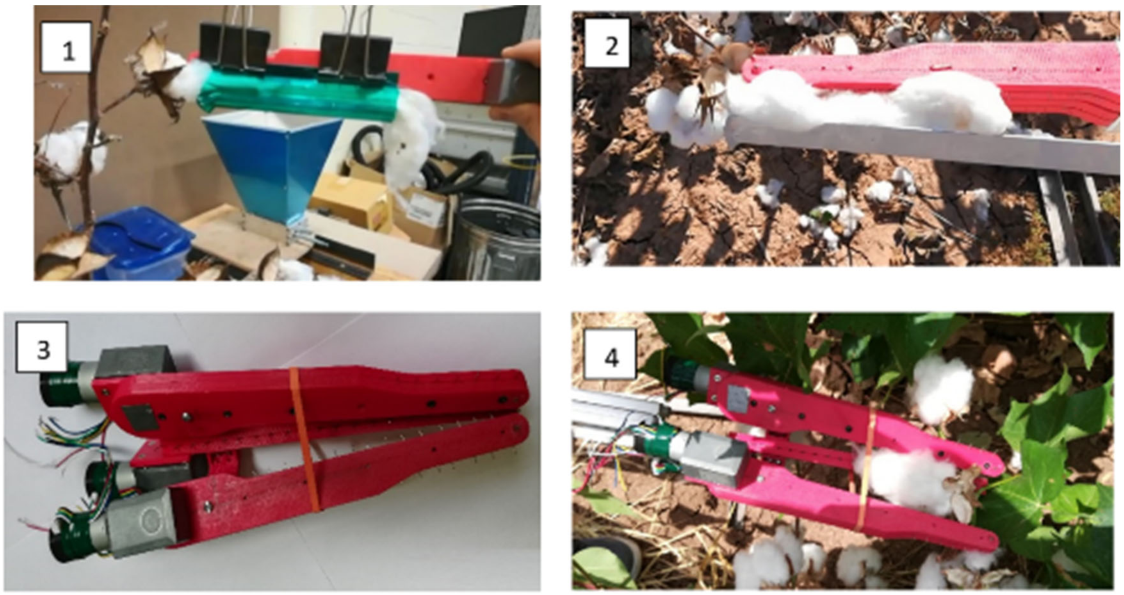

Figure 2. image 1: one-finger end-effector, image 2: one-finger end-effector, images 3, 4: Three-finger end-effector. Gharakhani and Thomasson (2021).

<u>Autonomous Cotton Boll Removal</u>

Fue et al. (2020) used a stereoscopic camera, machine vision processing, a deep learning network model (YOLOv3) and an embedded computer to manage computation of the images to identify cotton bolls in the field. A red rover was used as the platform for testing the system as illustrated in Figure 3. Results have shown that bolls were identified and located with a high level of confidence using one camera looking downward with sparse foliage later in the season.

Cotton boll images used for training the YOLOv3 deep neural network (DNN) model were augmented 27 times using CLoDSA. CLoDSA is 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.

The platform (Husky from Clearpath Robotics) noted in use by Maja et al. (2021) for weed control is designed to be retrofitted with different manifolds that performs specific task, e.g. spraying, scouting (having multiple sensors), phenotyping, weeding, harvesting, etc. 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). Preliminary results on the performance of the developed mobile robot platform for cotton harvesting shows an average of 57.4% success rate in harvesting locks that are about half an inch close to the harvester nozzle. Further design enhancement was done in 2020 where a stripper mechanism was added and placed on the side of Husky (See Figure 4). The new design replaced the suction cap with a rolling stripper similar to a stripping machinery and used the same suction motor to move the harvested bolls to the bucket previously used in the first harvester prototype. The stripper on the side is driven by a single 24V motor. Current efforts are examining the possibility of using the Husky as a once-over harvester.

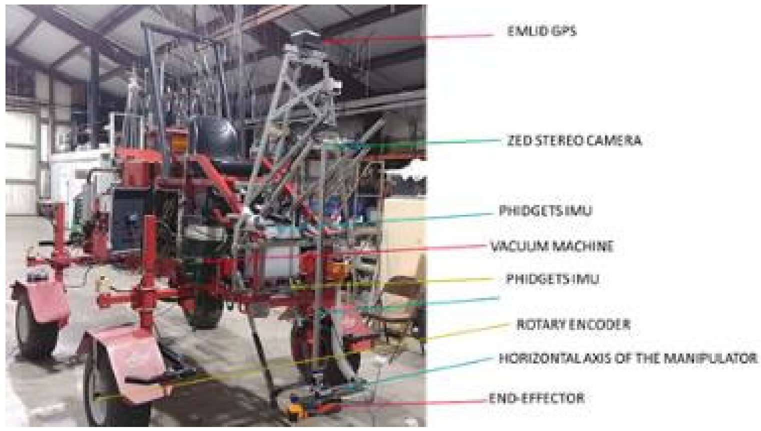

Figure 3. Red Rover platform for testing cotton harvesting system (Fue et al., 2020).

Currently there are additional harvest concepts being discussed. One 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. Another concept is rather than have multiple single row units, "intelligent" headers could be developed to allow some similar to the "red rover" in Figure 3 be adapted to a multiple row system still capable of multiple harvest passes through the same field. Additional concepts are under development and the economic models described in a later section will be an important component in ranking various concepts.

There is a clear interest in developing a harvest system that is capable of multiple passes through the field as it is anticipated that more frequent harvest will increase the quality of the cotton and reduce the risk of harvest loss due to severe weather events relative to a single end of year harvest event. 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. 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. In 2018, all sites except for Georgia conducted the harvest treatments across two varieties, and in 2019 all sites had two varieties. Additional details can be found in Griffin et al. (2019; 2021). In a majority of the sites and years, color grades were consistently higher for the frequently harvested cotton relative to a single harvest at the end of the season. Yield impacts were not as consistent; however, in 2018 there was a significant yield advantage to the frequently harvested treatment compared to the end-of-season harvest treatments as hurricane Michael impacted the Georgia site. All of the data sets from this study can be used in economic modeling of different cotton harvest systems.

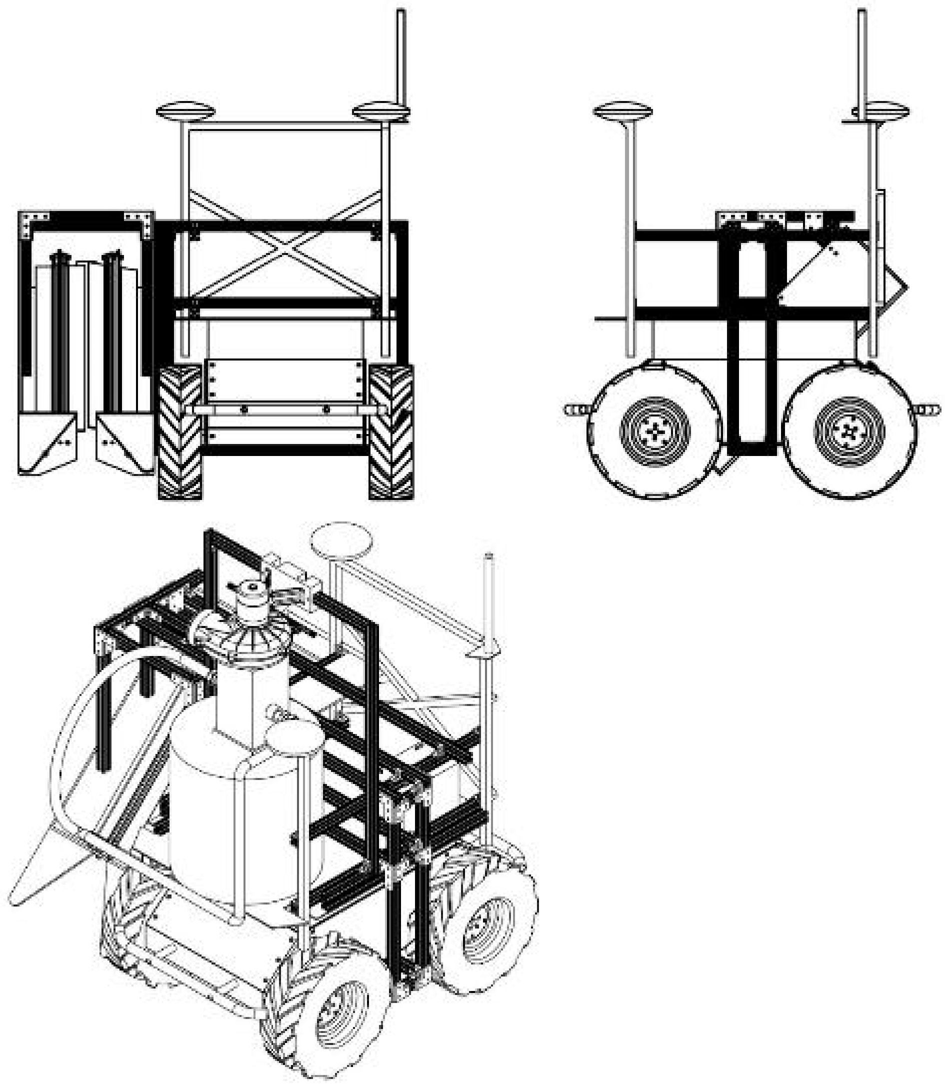

Figure 4. The next generation of Cotton Harvesting Autonomous Platform.

Economic Models of Robotic Cotton Harvest

Two distinct methodologies have been applied to support economic analysis of robotic versus current mechanical harvest systems. 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://shiny.agmanager.info/cottonBots/

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

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 the 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 are needed to replace the status quo such that harvest is completed on the 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.

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 may be advisable. In stripper harvested areas, use of robotic harvesters may allow for the avoidance of the desiccation pass, which in turn would lower production costs.

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.

Warehouse Operations

Several industries have automated warehouse operations that range from completely autonomous materials handling to collaborative robots.

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

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. One area very specific to cotton is the potential for autonomous harvest systems. A conclusion from the harvest study illustrated that under certain weather conditions the ability to frequently harvest will increase yield and fiber quality. 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. Enabling technologies that will accelerate the speed of agricultural automation include open source codes systems such as ROS and the increased availability of image data sets specific to cotton to train machine vision systems for pest detection and identification of cotton bolls.

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. The ability to simulate different field conditions (e.g., lighting, crop size, and soil background) to augment image data sets is also a priority.

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	Themal 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	

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 and August of 2020: 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.

References

Barnes, E., K. Hake, J. Devine, T. Griffin, G. Ibendahl, G. Rains, K. Fue, J. Maja, M. Bruce, J. Thomasson, J. Griffin, E. Kimura, G. Morgabrucen, B. Ayre, and M. Pelletier. 2019. Initial possibilities for robotic cotton harvest. Beltwide Cotton Conferences, New Orleans, LA, January 8-10, 2019. Pp. 133-143. National Cotton Council, Memphis, TN.

Barnes, E., G. Morgan, K. Hake, J. Devine, R. Kurtz, T. Griffin, G. Ibendahl, G. Rains, J. Snider, K. Fue, J. Maja, M. Bruce, A. Ermanis, D. Daly, C. Chiu, M. Cutulle, M. Burce, J. Griffin, J. Thomasson, E. Kimura, B. Ayre, T. Raper, S. Young, M. Pelletier, J. Wanjura, and G. Holt. 2020. Current and Potential robotic applications to improve cotton production. Beltwide Cotton Conferences, Austin, TX, January 8-10, 2020. Pp. 334-357. National Cotton Council, Memphis, TN.

Bauer, P.J., J.R. Frederick, J.M. Bradow, E.J. Sadler, and D.E. Evans. 2000. Canopy photosynthesis and fiber properties of normal and late-planted cotton. Agronomy Journal 92(3):518-523.

Bradow, J.M. and P.J. Bauer. 1997. Fiber-quality variations related to cotton planting date and temperature. Beltwide Cotton Conference (pp. 1491-1495). New Orleans, LA: National Cotton Council of America, Memphis, TN.

Bradow, J.M., and G.H. Davidonis. 2000. Quantitation of fiber quality and the cotton production-processing interface: A physiologist's perspective. Journal of Cotton Science 4:34-64.

Burce, M., J.M. Maja, E. Barnes. 2019. Adaption of Mobile Robot Platform for Cotton Harvesting. Beltwide Cotton Conferences, New Orleans, LA, January 8-10, 2019. National Cotton Council, Memphis, TN.

Davidonis, G.H., A.S. Johnson, J.A. Landivar, and C.J. Fernandez. 2004. Cotton Fiber Quality is Related to Boll Location and Planting Date. Agronomy Journal 96, 42-47.

Daystar, J.S., Barnes, E., Hake, K., & Kurtz, R. (2017). Sustainability trends and natural resource use in U.S. cotton production. BioResources 12(1), 363-392.

Fue, K., E. Barnes, W. Porter, GC Rains, 2019. Visual Control of Cotton-picking Rover and Manipulator using a ROS-independent Finite State Machine. Annual ASABE Conference, Paper No. 1900779 Boston, MA, DOI: https://doi.org/10.13031/aim.201900779..

Fue. K., W. Porter, E. Barnes, C. Li and G. Rains. 2020. Center-Articulated Hydrostatic Cotton Harvesting Rover Using Visual-Servoing Control and a Finite State Machine. Electronics 2020, 9, 1226; doi:10.3390/electronics9081226

Gharakhani, H. and A. Thomasson. 2020. Robotic cotton harvesting and field fiber seed separation approaches and challenges. Beltwide Cotton Conferences, Austin, TX, January 8-10, 2020, pp. 768-773.

Gharakhani, H. and A. Thomasson. 2021. Design and test different end-effectors for robotic cotton harvesting. Beltwide Cotton Conferences, January 5-7. In Press.

Griffin, J., G. Morgan, E. Kimura, J. Snider, and E. Barnes. 2019. Impacts on cotton fiber quality from multi-pickings compared to traditional single bass harvest systems. Initial possibilities for robotic cotton harvest. Beltwide Cotton Conferences, New Orleans, LA, January 8-10, 2019.

Griffin, J., G. Morgan, R. Hardin, E. Kimura, J. Snider, T. Raper, and E. Barnes. 2021. Multiple-pass harvest comparted to single pass harvest methods effect on yield and fiber quality. Beltwide Cotton Conference Poster, January 5-7. In Press.

Hauck, J.W., 2019. Robotic agricultural protection system. U.S. Patent 2019/0069535 A1.

Jackson, R. D., Idso, S. B., Reginato, R. J., & Pinter Jr., P. J. (1981). Canopy temperature as a crop water stress indicator. Water Resour. Res. 17(4):1133-1138.

Kothari, N., J. Dever, S. Hague, and E. Hequet. 2015. Evaluating intraplant cotton fiber variability. Crop Science 55:564-570.

Kothari, N., S. Hague, L. Hinze, and J. Dever. 2017. Boll Sampling protocols and their impact on measurements of cotton fiber quality. Industrial Crops and Products 109, 248-254.

Lamm, R.D., D.C. Slaughter, and D.K. Giles. 2002. Precision weed control system for cotton. Transactions of the ASAE 45(1):231-238.

Limbasiya, Y.G., and J.P. Maheta. 2015. Mechanism design of cotton picking gripper. International Journal of Advance Research in Engineering, Science & Technology (IJAREST), ISSN(O):2393-9877, ISSN(P): 2394-2444 2(5):8pp.

Lu, Y., and S. Young. 2020. A survey of public datasets for computer vision tasks in precision agriculture. Computers and Electronics in Agriculture. 178 (2020) 105760. https://doi.org/10.1016/j.compag.2020.105760

Maja, J.M.J., M. Cutulle, J. Enloe, J. Weber, and E.M. Barnes. 2021. Mobile Robot Weeder and Harvester Prototype for Cotton Production. Proceedings Beltwide Cotton Conferences.

Meyer, L.A. 2016. The World and U.S. Cotton Outlook for 2016/17. Presented at the Interagency Commodity Estimates Committee, Agricultural Outlook Forum, USDA, Office of the Chief Economist, February 26, 2016. https://www.usda.gov/oce/forum/2016_speeches/meyer.pdf

Murray, C.L., and M.E. Barker. 2018. Autonomous robotic agricultural machine and system thereof. United States Patent No. 9,891,629 B2. Feb. 13, 2018.

Mwitta, C. and G.C. Rains. 2021 Real-time weed detection and removal using deep learning and laser. Proceedings of the Beltwide Cotton Conferences. In Press.

Nagasaka, Y., Q. Zhang, T. Grift, Y. Knetani, N. Umeda, and T. Kokuryu. 2004. Control system design for an autonomous field watching-dog robot. Automation Technology for Off-Road Equipment, Proceedings of the 7-8 October 2004 Conference (Kyoto, Japan). ASAE Publication Number 701P1004. Eds. Q. Zhang, M. Iida, A. Mizushima.

NCC. 2018. U.S. Cotton ten year sustainability goals - Pathways to progress. National Cotton Council of America, Cotton USA, Cotton Incorporated. Retrieved from https://cottontoday.cottoninc.com/wp-content/uploads/2018/02/Cotton_Sustainability_2018_low.pdf

Pelletier, M.G., Wanjura, J.D. and Holt, G.A. 2020. System Design of a Distributed Controller for a Multi-Node Machine-Vision based Plastic Contamination Detection and Ejection System. AgriEngineering, (in press).

Pelletier, M.G., Wanjura, J.D. and Holt, G.A. 2019a. Embedded Micro-Controller Software Design of a Cotton Harvester Yield Monitor Calibration System. AgriEngineering, 1(4): 485-495.

Pelletier, M.G., Wanjura, J.D. and Holt, G.A. 2019b. Man-Machine-Interface Software Design of a Cotton Harvester Yield Monitor Calibration System. AgriEngineering, 1(4): 511-522.

Pelletier, M.G., Wanjura, J.D. and Holt, G.A. 2019c. Electronic Design of a Cotton Harvester Yield Monitor Calibration System. AgriEngineering, 1(4): 523-538.

Pitla, S., S. Bajwa, S. Bhusal, T. Brumm, T. Brown-Barandl, D. Buckmaster, I. Condotta, J. Fulton, T. Janzen, M. Karke, M. Lopez, R. Moorhead, M. Sama, L. Schumacher, S. Shearer, and A. Thomasson. 2020. Ground and Aerial Robots for Agricultural Production: Opportunities and Challenges. CAST Issue Paper 70. https://www.cast-science.org/wp-content/uploads/2020/11/CAST_IP70_High-Tech-Ag-1.pdf

Rao, USN. 2013. Design of automatic cotton picking robot with machine vision using image processing algorithms. 2013 International Conference on Control, Automation, Robotics and Embedded Systems (CARE), 16-18 December, Indian Institute of Information Technology, Design and Manufacturing, Jabalpur India. Institute of Electrical and Electronics Engineers, Inc.

Salfer J., M. Endres, W. Lazarus, K. Minegishi, B. Berning. 2019. Dairy Robotic Milking Systems – What are the Economics? DAIReXNET. https://dairy-cattle.extension.org/2019/08/dairy-robotic-milking-systems-what-are-the-economics/

Sistler, F.E. 1987. Robotics and Intelligent Machines in Agriculture. IEEE Journal of Robotics and Automation RA-3(1):3-6.

Slaughter, D.C. D.K. Giles, and D. Downey. 2008. Autonomous robotic weed control systems: a review: computers and electronics in agriculture 61:63–78.

Sui, R., J.A. Thomasson, J. Hanks and J. Wooten. 2008. Ground-based sensing system for weed mapping in cotton. Computers and Electronics in Agriculture 60:31–38.

Valjaots, E., H. Lehiste, M. Kiik, and T. Leemet. 2018. Soil sampling automation using mobile robotic platform. Agronomy Research 16(3):917-922. https://doi.org/10.15159/AR.18.138

Vories, E.D., A.S. Jones, C.D. Meeks, and W.E. Stevens. 2019. Variety effects on cotton yield monitor calibration. Applied Engineering in Agriculture 35(3): 345-354

Wang, M., J. Wei. J. Yuan, and K. Xu. 2008. A Research for Intelligent Cotton Picking Robot Based on Machine Vision. Proceedings of the 2008 IEEE International Conference on Information and Automation June 20 -23, 2008, Zhangjiajie, China.

Wanjura, J.D., E.M. Barnes, M.S. Kelley, and R.K. Boman. 2015. Harvesting (book chapter) in Cotton, 2nd Edition, D.D. Fang and R.G. Percy, Editors. Agronomy Monograph 57.Wanjura, J.D., M.G. Pelletier, G.A. Holt, M.S. Kelley. 2015. A harvester based calibration system for cotton yield monitors. In Proc. 2015 Beltwide Cotton Conf. pp 635-647. Memphis, TN: National Cotton Council.

Wanjura, J.D., M.G. Pelletier, G.A. Holt, M.S. Kelley. 2016. Reliability testing of an on-harvester cotton weight measurement system. In Proc. 2016 Beltwide Cotton Conf. pp 658-670. Memphis, TN: National Cotton Council.

Wanjura, J.D., E.M. Barnes, M.G. Pelletier, G.A. Holt. 2017. New technologies for managing cotton modules. In Proc. 2017 Beltwide Cotton Conf. pp 420-432. Memphis, TN: National Cotton Council.

Wanjura, J.D., E.M. Barnes, G.A. Holt, and M.G. Pelletier. 2018. New technologies for managing cotton modules and harvest information. In Proc. 2018 Beltwide Cotton Conf. pp 841-856. Memphis, TN: National Cotton Council.

Westwood JH, Charudattan R, Duke SO, Fennimore SA, Marrone P, Slaughter DC, Swanton C, Zollinger R. 2018. Weed Management in 2050: Perspectives on the Future of Weed Science. Weed Sci. 10.1017/wsc.2017.78