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Ground and Aerial Robots for Agricultural Production: Opportunities and Challenges

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Ground and aerial robots combined with artificial intelligence (AI) techniques have potential to tackle the rising food, fiber, and fuel demands of the rapidly growing population that is slated to be around 10 billion by the year 2050. (Photo illustration by Megan Wickham with images from Santosh Pitla and Shutterstock.)

Abstract

Crop and animal production techniques have changed significantly over the last century. In the early 1900s, animal power was replaced by tractor power that resulted in tremendous improvements in field productivity, which subsequently laid foundation for mechanized agriculture. While precision agriculture has enabled site-specific management of crop inputs for improved yields and quality, precision livestock farming has boosted efficiencies in animal and dairy industries. By 2020, highly automated systems are employed in crop and animal agriculture to increase input efficiency and agricultural output with reduced adverse impact on the environment. Ground and aerial robots combined with artificial intelligence (AI) techniques have potential to tackle the rising food, fiber, and fuel demands of the rapidly growing population that is

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slated to be around 10 billion by the year 2050. This Issue Paper presents opportunities provided by ground and aerial robots for improved crop and animal production, and the challenges that could potentially limit their progress and adoption. A summary of enabling factors that could drive the deployment and adoption of robots in agriculture is also presented along with some insights into the training needs of the workforce who will be involved in the next-generation agriculture.

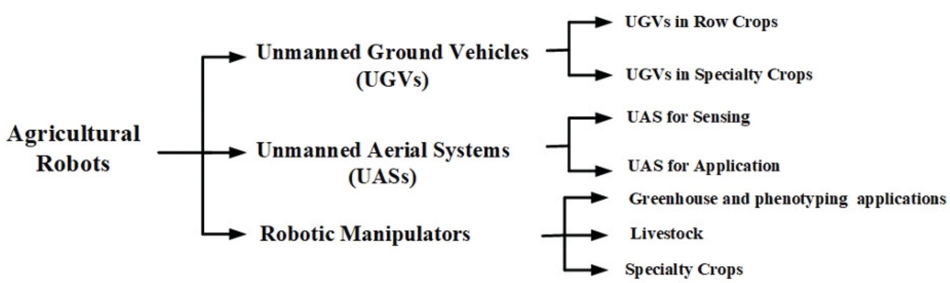

Figure 1. Classification and Important Application Domains of Agricultural Robots.

Introduction and Background

The increase in demand for food, feed, fiber, and energy is inevitable, given the projected population increase in the coming decades as well as increasing affluence in developing economies of the world. Food production has to increase by approximately 70% to feed 9.7 billion people by the year 2050 (Bruinsma 2009). Advancements in biotechnology are seen as one of the potential solutions for increasing food production to address these impending local and global demands (Tilman et al. 2001). Efficiently managing crop inputs such as seeds, chemicals, fertilizers, and labor to boost yields and quality while minimizing environmental impacts is important to support the on-going biotechnology efforts. Agricultural robots combined with digital agriculture techniques are seen as an effective method for monitoring large acreages to assess crop conditions, increase precise management of crop inputs in row and specialty crops, allow efficient harvesting in specialty crops, evaluate high yielding and resource efficient crop varieties in research plots, and be more efficient in managing livestock (Chen 2018). Motivated by these opportunities, numerous teams around the world have been working on research and development of various types of robotic solutions for crop and animal farming. Figure 1 provides a broad classification of such agricultural robots. Ground robots or unmanned ground vehicles (UGVs) and aerial robots or Unmanned Aerial Systems (UASs) are used in both row-crops and specialty crops. Robotic manipulators (robotic arms) on the other hand are primarily used in dairy, specialty crop, and greenhouse applications. Each of these robot categories along with some examples are discussed in detail in the next section.

Ground Robots

Changing weather patterns and the need to boost agricultural productivity require a paradigm shift in how field operations are accomplished. For example, UGVs could perform repetitive operations with great precision for up to 22 hours per day (with a small portion of that time for service and maintenance) which could substantially increase the daily work output compared to human-operated machinery. Deploying UGVs for crop and livestock production is a tremendous opportunity to boost productivity. However, deploying UGVs that are capable of decision making and working in remote harsh field conditions intelligently and safely comes with both complex engineering and socio-economic issues. Some important engineering challenges include: (1) designing effective control architectures and artificial intelligence (AI) algorithms for operating individual and a fleet of UGVs with and without humans in the loop and (2) designing and deploying robots to work faster and more gently than human labor when interacting with plants and animals. Some important socio-economic challenges include: (1) Fear associated with robots in terms of replacing human labor (2) Economic feasibility of robots for both large and small acreage farms (3) Liability, security, and data privacy concerns associated with UGVs.

Aerial Robots

UASs have been explored as technology tools of great value for agricultural production. One of the challenges to the greater exploitation of UAS in agricultural production is the computational resources required to exploit all the data and information they can obtain. The ability to simply rise above the crop or livestock and see what cannot be seen from the ground provides opportunity to determine crop and animal health more easily. For example, the ability to examine the ground from the air above enables detection of plant emergence without physically entering the field, or provides a more efficient way to count or analyze livestock. UASs can quickly determine soil moisture and crop health over the entirety of the field with great precision. Similarly, UAS-based systems can be used to measure animal temperature quickly and non-invasively, and thereby identify which animal might be in heat or have an illness. As miniaturized sensors, such as microwave radiometers, short-wave infrared sensors, and LiDARs (light detection and ranging), are integrated with UASs, opportunities to measure soil moisture and crop health precisely, map field topography, and locate irrigation system leaks on a field-by-field scale, will become affordable to the producer. LiDARs can measure plant height, often an indicator of crop health. LiDAR data can also be used to measure livestock growth and health. As researchers develop algorithms to exploit the increased spatial resolution of low-flying UAS, increased opportunities will occur to reduce inputs to crops by applying inputs to only areas where and when the input is needed. Crop problems such as diseases could also be detected earlier before they become widespread. Better spatial resolution of livestock images leads to enhanced ability to detect needs of each animal individually.

UASs, however, also suffer from some important limitations. One of the challenges to exploiting UASs in agriculture production will be weather related—most small UASs cannot operate in high winds or medium precipitation. Another challenge will be the acquisition and maintenance of computing resources to rapidly process images into information. Determining the optimal suite of UASs and payloads is a challenge. Calibration of sensors and data to ensure the quality of the data collected, and useful metadata generation are some of the other challenges. The opportunity to add another data collection system—an UAS—to an existing suite of data collection systems (e.g., yield monitors and spray controllers) creates a challenge in data integration. UAS allows collection of data over the entirety of a field, as opposed to a point sample collection with a soil moisture probe or a monitor on a feed or water trough.

Producers interested in using aerial robots on their farms will need to decide whether to operate their own UAS or hire a UAS service provider. Service providers can standardize operational variables to meet data quality and application needs and amortize the cost of the technology over more users per unit time, whereas self-operation provides greater flexibility in use and access. Similarly, there are trade-offs in running analyses locally or using cloud computing.

Robotic Manipulators

Robotic manipulators are mechanisms that manipulate objects in a given work-space and are typically found in industrial automation applications for performing automated movements Robotic manipulators are now becoming indispensable for automating precise repetitive motions in both animal and crop production. Robotic milking stations used in dairy production are good examples of manipulator type robotics that are commercially available. These automatic milking stations use proximity sensors, robotic arms and suction cups for automating the milking process (Broucek and Tongel 2015). Robotic arms are a type of manipulators that mimic hand movements of a human for picking and placing of objects. In crop production, robotic arms are predominantly deployed in orchard and greenhouse applications. In orchards, picking of fruit is accomplished by mounting robotic arms on either a ground robot or other farm vehicles. The ground robot navigates to the fruit tree and the robotic arm performs the operation of picking the fruit. Robotic arms have been developed for picking vegetables such as tomatoes, mushrooms, and cucumbers (Van Henten et al. 2002; Reed et al. 2001). Apple and cherry harvesting robot arms can be found in the literature (Davidson et al. 2015; Burks et al. 2005; Silwal et al. 2014). Very recently, Atefi and colleagues (2019) have shown robotic arms have also been used for leaf grasping of corn and sorghum plants for phenotyping applications. While robotic milking stations are commercially available, robotic manipulators for specialty crop and greenhouse applications are still in research and development phase. Robotic arms used in orchards are challenged by occlusion of fruit (one fruit in front of another) and varying lighting conditions which adversely effects the time required for picking the fruit (Davidson et al. 2015). The speed of picking a fruit from a tree is still relatively slow compared to manual picking. Improved motion planning and machine vision algorithms, and AI techniques are needed to improve the fruit picking efficiency of robotic arms. In crop production (both row-crop and specialty), robotic manipulators are typically mounted on ground robots, hence further discussion on the opportunities and challenges of this category of robots for specific applications is presented in the section on crop producton. Opportunities and challenges of robotic manipulators in animal agriculture is presented in the section on animal agriculture..

Ground and aerial robots could be working as a team to identify and solve problems in the field, whereas robotic manipulators could be milking the cows in the barn in a connected farm setting (see Figure 2). UASs could identify larger issues at field scale, whereas, UGVs could be navigating autonomously to specific locations in the field for high-resolution fertilizer or pesticide application to solve the issue. Seamless information exchange happens among ground and aerial robots with a cloud-based brain or decision support. Computationally intensive operations could be done on the cloud for minimizing computational loads on the robotic vehicles. In an integrated animal and crop production connected farming system such as the one shown in Figure 2, sensor and process data from both the field and animal barn is sent to the cloud for further analytics and improved decision-making, and these decisions are sent back to the robotic applicators for implementation in the field. Robotic manipulators housed in the barn could be milking the cows, providing right amount of feed, monitoring the environmental conditions, and measuring physical attributes of the livestock.

Ground and Aerial Agricultural Robots

Crop Production

Row crops

Row crop production practices aim to optimize productivity through maximizing yields and minimizing cost. Gains in yield are commonly achieved through advances in genetics, improvement of soil health, and optimal management of inputs (i.e., timing, rate and placement of nutrients, crop protectants and water). Mechanization, the historical trend towards larger and more advanced equipment and consolidation of smaller farms, reduces labor costs through economies of scale. Automation has the potential to not only augment current production practices through optimization of crop inputs, but also serves as a disruptive technology that has the potential to change the farming paradigm by reverting to more scale neutral technologies and perhaps Farming-as-a-Service (FaaS).

The demand for automation in the rapidly evolving agriculture equipment industry is moving towards the deployment of large autonomous vehicles. With the continual increase in engine power and the size of manned equipment, there is concern associated with removing the human operator from the field environment—safety and liability. Liability of large autonomous machinery is a driving factor for thinking small. In the event of a malfunction or collision, small UGVs could cause less damage compared to an UGV with high gross vehicle weight. The concept of replacing conventional large agricultural machines with multiple small-to-medium-sized UGVs is feasible given the advances in autonomous technologies (Blackmore et al. 2004; Higuti et al. 2019; Troyer, Pitla, and Nutter 2016). UGVs will operate 22 hours per day to compensate for the reduced work rate of smaller equipment, and to minimize environmental impact through precise management of crop inputs. Soil compaction that is associated with the use of larger manned machinery, will be potentially alleviated with the use of small autonomous equipment (Shearer and Pitla 2013). Low gross vehicle weights and optimized field travel paths of UGVs will contribute to reduced soil compaction. Additionally, in a system where one large piece of equipment is used for field operations and if that equipment is down for repair and maintenance, the complete operation is stopped. However, in the case where multiple UGVs are used, even if one or two UGVs are down for repair and maintenance, other UGVs can

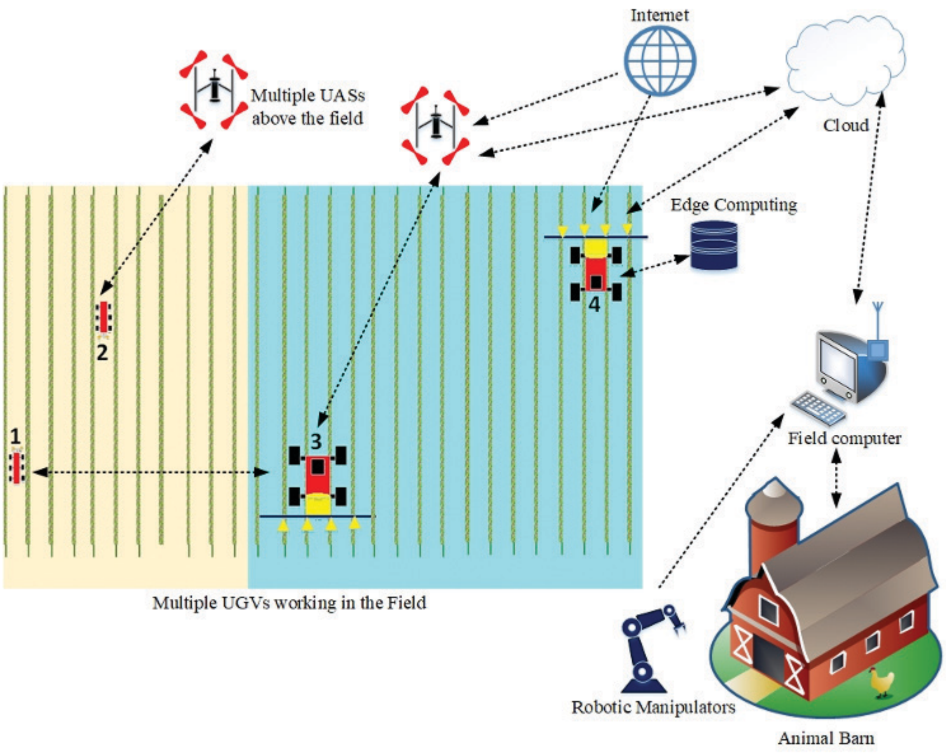

Figure 2. UGVs, UASs, and Robotic Manipulators in a Connected Farm.

still continue to work without halting the entire operation and minimize risk (Anil et al. 2015). UGVs could be operating in large numbers in a swarm configuration in the future (Project Xaver: https://www.fendt.com/int/xaver; Swarm Farm: https://www.swarmfarm.com). In addition to minimizing the risk, one of the other major goals of using these UGVs is to reduce the scale of management to a small land unit or potentially to an individual plant.

Concept driverless tractors have been showcased by both established equipment manufacturers (CNH Industrial 2017; Farm Equipment 2019, 2020; Raven Autonomy 2020) and start-up companies in last few years. A list of commercial robot prototypes offered by start-up companies can be found here: https://builtin.com/robotics/farming-agricultural-robots. Some companies are offering advanced row-crop robotic solutions in the form of Farming-as-a-Service (FaaS: Sabantaoag.com). Researchers are developing robotic prototypes for row crop field applications such as autonomous weed management, seeding, and plant phenotyping (Murman 2019; Young, Kayacan, and Peschel 2019; Yuan et al. 2019; Zhang et al. 2016). Multi-purpose robotic platforms that could be used throughout the growing season are being explored. This is analogous to a tractor being used for multiple field operations such planting, tillage, and grain haulage. A UGV that could be utilized throughout the growing season for multiple operations could be cost effective, however, there are complexities in terms of hardware and software modularity and system performance that need to be resolved (Fountas et al. 2020). Figure 3 shows a 60 horsepower multi-purpose UGV called "Flex-Ro" 3 phenotyping a soybean field. For this application, Flex-Ro was equipped with cameras, portable spectrometers, and ultrasonic height sensors to characterize physical traits of different soybean varieties (Murman 2019).

Figure 3. Flex-Ro, a 60 HP UGV, collecting soybean plot information. (Photo credit: Santosh Pitla, University of Nebraska-Lincoln.)

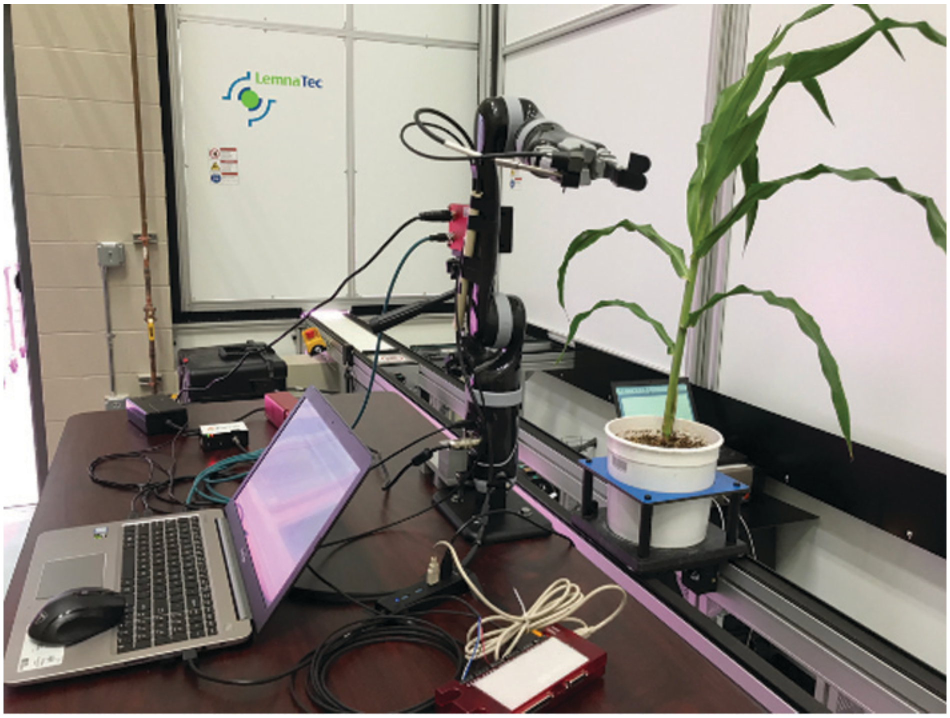

Figure 4. Robotic Arm phenotyping a corn plant in a green house. (Photo credit: Abbas Atefi, University of Nebraska-Lincoln.)

Robotic manipulators for corn and sorghum plant phenotyping are also under development (Atefi et al. 2019; Bawden et al. 2016). Figure 4 shows a phenotyping robotic arm that is capable of grasping an individual leaf to measure leaf chlorophyll, leaf temperature, and moisture. In the future, this type of robotic arms could be mounted on UGVs to improve the overall capabilities of the robotic platforms. For example, a robotic arm mounted on an UGV could be collecting leaf and soil samples for both in-field and laboratory analysis. However, challenges exist for the deployment of UGVs in current row-crop production settings. The economics of autonomous operation play a big role in the adoption of UGVs. Cost comparisons between conventional agricultural equipment and UGVs are beginning to emerge in literature (Shockley, Dillion, and Shearer 2019), however detailed economic and life cycle analyses of UGV systems or swarms are required. Control architectures for stand-alone and fleet level operation of UGVs are still evolving (Posselius et al. 2016). These control architectures are important for intelligent operation of machinery in a field environment whether they are working by themselves or working in a fleet configuration. Effective control architectures and AI algorithms will provide the ability for the UGVs to differentiate between obstacles, crop, and collaborative entities (e.g., humans or other robots) to accomplish field tasks (Jasiński et al. 2016). AI enabled UGVs will allow the machine to diagnose itself when the operator is not in the loop. For example, when crop residue plugs a tillage tool and when a nozzle plugs on a spray boom, or if a bearing goes out on a planter row unit, the UGV has to diagnose and resolve the problem on its own (Shearer and Pitla 2013). Key sensing components of these control architectures are sensors such as LiDARs and multi-spectral cameras were historically expensive and required significant computing resources. However, with the proliferation of sensors in the driverless on-road vehicle sector, the cost of sensing and computing devices (e.g., GPUs) is projected to decrease in the coming years. AI technologies are advancing at a faster pace; however, the availability of agricultural training datasets is limited. More publicly available training datasets of agricultural environments and open source tools are needed. Internet connectivity will become increasingly important to the logistics of servicing this equipment in the field (e.g., refilling with seed, nutrients, crop protectants and fuel) as well as coordinating the activity of fleets or swarms of UGVs. Safety standards for the operation of autonomous agricultural field machinery are still in nascent stages and require effective public-private partnerships to develop benchmarks and regulations to complement the advancements in UGV systems. The standardization process will likely be informed and influenced by the on-road transportation standards, particularly for larger equipment that may need to be transported on public roads (ANSI 2020).

While UGVs are aimed at automating both production activities and sensing processes, UASs are so far used primarily for sensing applications. The predominant use of UASs in row crop production has been for general scouting (Stehr 2015). Weed, pest, and disease infestation resulting in observable changes in row crop color or physical structure can readily be observed with consumer-grade UASs equipped with standard cameras (Peña et al. 2015; Vanegas et al. 2018; Wang et al. 2020). UASs are frequently used to quantify and document crop damage for making insurance claims (Luciani et al. 2020).

A more advanced, but less common, use for UASs is to estimate production parameters using image-based remote sensing. Visible, multispectral, or thermal cameras deployed on multi-rotor or fixed-wing UASs are used to collect a series of images along prescribed flight paths at high spatial resolutions (1–10 cm per pixel). Figure 5 shows an example of a UAS system collecting multispectral images of soybean plots. Images are generally stitched into orthomosaic maps covering entire fields that can be overlaid with other data layers in geographical information systems (GIS) or farm management software (FMS). Data are interpreted and used to prescribe management operations and/or predict/explain observed spatial variability in productivity.

Research applications expand upon image-based remote sensing by incorporating more expensive sensing and data analysis methods, including spectral sensing (Hamidisepehr and Sama 2019; Varela et al. 2018) and three-dimensional modeling (Dvorak et al. 2020). However, UASs equipped with research-grade sensors can frequently cost more than a well-equipped 100 HP tractor, which has limited use in production agriculture given the financial risk associated with deployment. UAS technology is advancing at fast pace and companies are just beginning to offer UAS that can perform material application (e.g., spot spraying of chemicals: https://www.dji.com/t16).

Numerous challenges prevent widespread adoption of UASs in row crop production. Prior to early 2010s, platform technology was the critical barrier that limited the use of UASs to research applications. Significant advances in battery technology and autopilot control have since made consumer UAS technology feasible, although cost still presents an is-

Figure 5. A Multirotor UAS collecting multispectral images of soybean plots. (Photo Credit: Michael Sama, University of Kentucky.)

sue. Between 2012 and 2016, researchers and producers commonly referenced constraints posed by Federal regulations on UASs operating in the National Airspace System were commonly referenced by researchers and producers as a bottleneck for integration into standard production practices. Regulations have since evolved but are still in their infancy and continue to restrict usefulness in large-scale row crop production. For example, deployment of fully autonomous UASs remains prohibited, and operating beyond line of site, above the stipulated altitude, or at night requires waivers that producers or crop consultants with limited experience may not be able to readily obtain.

Logistical challenges include a wide range of aspects such as platform endurance and durability, availability of ground reference data, and data throughput. Multi-rotor UASs tend to be easier to operate and deploy sensor payloads than fixed-wing UASs but cannot cover areas as large or as quickly as fixed-wing UASs. Both types of platforms cannot typically be used when precipitation or high winds are present. When used to collect remotely sensed data, calibrating sensors to parameters of interest remains a challenge to turn-key implementation—partly attributed to varying environmental conditions and the need for adequate ground reference data at field scale. While the recent trend towards cloud-based data aggregation and processing has improved data throughput, remote sensing data collected with UASs tends to produce large data files that can be difficult to process and manage.

The limited number of UAS manufacturers may also present future challenges to increased adoption of UASs. Nearly three-quarters of consumer UASs are supplied by a single rotor-craft manufacturer and no major consumer UAS manufacturer exists within the United States, which interestingly is in sharp contrast to military UASs. Agricultural equipment manufacturers have been predictably (and justifiably) slow in incorporating UAS-based products into their offerings as they transition from selling only conventional equipment to also providing technology and data solutions.

Economics are the ultimate challenge of incorporating UASs into standard production practices. Regional and national scale research is needed to demonstrate the applicability of a given UAS-deployed technology towards current production practices. Very little data are available showing the economic benefit that UASs provide to row crop producers. Coordination between UAS and sensor manufacturers and independent researchers will be critical for gaining public's confidence in the economics and practicality of this emerging technology.

Orchard and Specialty crops

Agricultural mechanization and automation have made a tremendous positive impact around the world in reducing farm labor requirements, optimizing input utilization, and increasing crop yield and quality. However, the adoption of advanced technologies and machines in farming specialty crops including tree fruit orchards have been minimal. Many field operations such as weeding, tree training, pruning, flower and fruit thinning, and fruit and vegetable harvesting are still entirely done manually. As the farming industry faces continually decreasing availability and increasing cost of farm labor around the world (Gallardo and Brady 2015), specialty crop farming may not be sustainable if labor saving technologies are not adopted in the near future.

Research and development efforts for addressing the above challenges have been in place for several decades (e.g., weeding [Slaughter, Giles, and Downey 2008], harvesting [Silwal et al. 2017], and pruning work [He and Schupp 2018]) with only marginal success for commercial adoption to date. Some of the challenges to successful adoption include lack of desired speed, accuracy, and robustness as well as high cost of the technology. Recent innovations and advancement in robotic systems and technologies such as soft robotic hands, AI tools such as deep learning, and increasingly affordable parallel computing systems such as graphic processing unit (GPU) have provided new opportunities to overcome some of these challenges and develop practical automation and robotic solutions for specialty crop farming. In recent years, utilizing these advancements, various research institutions and private companies/startups around the world have been aggressively pursuing development of robotic systems for field operations in specialty crops including fruit orchards.

In tree fruit crops and many vegetable crops, harvesting is the most critical hurdle as it requires the largest seasonal labor and highest cost among all field operations (Silwal et al. 2017; Washington State Employment Security Department 2016). Because of the criticality of this field operation, there have been focused efforts around the world to improve harvesting of various fruit and vegetable crops including apples (Hohimer et al. 2019; Silwal et al. 2017), kiwifruit (Williams et al. 2019), strawberries (Xiong et al. 2019), and asparagus (Leu et a. 2017). Other efforts in developing robotic solutions for specialty crops include weeding and thinning in vegetable crops, field logistics (e.g., strawberry tray moving robots [Hayashi et al. 2010], bin dog [Ye et al. 2017]), precision chemical application based on the canopy needs (Oberti et al. 2016), crop canopy management and crop load management including pollination, training, thinning, and pruning. To take the full benefit of automation and robotic technologies in specialty crop farming, all labor-intensive operations need to be automated so that there is a uniform, long-term employment in farming rather than seasonal peaks of hard-working laborers.

A large amount of federal, state, commodity group, and venture capital funding has been invested in recent years for advancing automation and robotic solutions for specialty crops, creating a highly conducive environment for research and development. With these resources and efforts, we are closer than ever in making robotic systems a reality for these crops as evident by the commercial vegetable thinning efforts by Blueriver Technologies (acquired by John Deere in 2017, [John Deere 2017]), the first commercial harvest of apples by Abundant Robotics in New Zealand in March 2019 (Benson 2019), and a full-scale robotic apple harvester is being evaluated by Fresh Fruit Robotics (FFRobotics 2016). All of these examples illustrate that automated systems are beginning to be used on commercial farms. Figure 6 shows a robotic arm equipped with machine vision and AI algorithms picking apples.

UASs use in specialty crops such as orchards and vineyards has been investigated broadly. Some of the recent research and development efforts in this area include monitoring and assessment of crop status (Baluja et al. 2012; Poblete et al. 2017), identifying/detecting various issues in the field including new pest infestation (Albetis et al. 2017), operation of irrigation system (Chakraborty et al. in press), and monitoring the progress of various field management practices. Use of UASs in these activities can be referred to as a passive application as the platform is used just to collect data from the fields but not interact directly with the crop. Alternatively, active application is where tasks are performed in the field including precision spraying of chemicals (Faiçal et al. 2014), deterring birds from fruit crops such as wine grapes and blueberries (Bhusal et al. 2019), and crop pollination (Chechetka et al. 2017; Wood et al. 2013). Figure 7 presents an example of active application with UASs for deterring bird pests. These UAS-based techniques show good promise for specialty crop production as the industry is generally output-driven (meaning higher output with higher inputs, if needed), rather than input driven. Minimization approaches are generally employed in some other crops such as corn and wheat.

Figure 6. Apple Harvesting Robot. (Photo Credit: Manoj Karkee, Washington State University.)

Figure 7. UAS used for automated bird pest deterrence in vineyard. (Photo credit: Manoj Karkee, Washington State University.)

Some major challenges exist in using ground and aerial robots in orchard environments including lack of desired speed, accuracy, and robustness in outdoor environment. Variability and complexity of crop canopies, variable and uncertain weather, and variability (in shape, size, color, and so on) and delicacy of produce are some of the major challenges impacting the performance of robotic machines. One specific case related to complexity of crop canopies would be the occlusion of objects that are meant to be manipulated (e.g., harvested, pruned, or sprayed). For example, a harvesting robot faces the challenges of harvesting a fruit (e.g., apples, strawberries) being occluded and/or obstructed by leaves, branches, trellis wires, and trunks. Similarly, pruning in tree fruit crops is challenged by the complex orientation and position of branches needing to be removed in a tree canopy, whereas weeding in vegetable crops is challenged by the similarities between crop plants and the weed to be removed.

In recent years, there has been continuous improvement and adoption of tree fruit canopies to create structured, narrow crop canopies where all or most of the canopy parts (e.g., fruit and branches) are visible and accessible for robotic operation. However, even with the best possible architecture of apple trees available in the industry around the world, it has been difficult for the latest prototype robots to access and pick more than 80% of the fruits. Robots could be designed to be more dexterous to access and pick a larger percentage of fruits. However, farming requires simpler, but effective machines compared to other industries to keep the cost at affordable level and to be able to operate and supervise them in farms by workers with limited technical skills. Additionally, farmers should be able to fix the machines/robots quickly in remote field locations as they will be dealing with highly time sensitive operations like harvesting asparagus where a delay of a day might mean a huge loss in yield and/or quality of the produce. Further advancement and adoption of fruit cultivars and canopy architectures friendlier for robotic operation will play a key role for the wider success of robotic farming in these crops. Genetics, breeding, and crop physiological studies, in close collaboration with engineering studies, are crucial to make this happen.

Multi-purpose robotic machines could be an important opportunity for future research and development. Modular end-effectors could be designed such that different end-effectors could be installed in and taken out of a robotic machine to perform multiple field operations over the entire farming season using the same machine. For example, a robot for tree fruit orchards could be designed so the same machine could be used year-round for training trees, pruning branches, thinning flowers, pollinating flowers, thinning fruitlets, applying chemicals precisely, and harvesting fruit. Other crops such as vegetables (particularly organic) need efforts in developing robust solutions for weeding, thinning, and harvesting. In case of UASs, it is important that active operations like deterring birds or surgical application of chemicals be combined with regular crop monitoring operations.

In both row-crop and specialty crop production, system modularity is another big benefit that can be introduced into farming with automated/robotic systems. Farming with small robots that can work together in close collaboration (as a swarm) has been a new direction (Anil et al. 2015). With this model, all sizes and types of farms would be able to adopt the technology as smaller farmers could acquire just a few machines while larger farmers can acquire dozens of them or even hundreds of them as desired to fit the needs of their operations. For the successful implementation of swarm robotics, faster broadband connectivity in the fields would be important. These fields are generally located in the areas that are currently less connected and where mobile service providers have less incentive to expand because of the remoteness of the location and lack of consumer volume. Efforts like Farmbeats (Microsoft 2019) provide a potential opportunity for improving connectivity on farms. Federal initiatives such as the Rural Broadband Connectivity Act of 2018 (USDA 2018) and a sizable growth in connectivity consumption by farming industry to support the future of farming may considerably expand future broadband connectivity in farming areas. A detailed discussion on farm connectivity is presented in the section on farm connectivity.

The socio-economic implications of adopting new technologies are another crucial aspect to consider in developing and adopting robotic technologies in farming. In the public, and primarily in the communities dependent on the farming jobs being automated, there can be a fear of losing jobs when automation/robotics is introduced to specific industries/operations. These concerns exist in row and specialty crop production, and other non-farming activities as well. There is a huge shortage of labor in agriculture and it is expected to continue to worsen in the years to come (Gallardo and Brady 2015). If/when we are able to move to a completely automated or robotic farming in specialty crops, some people would obviously lose their jobs. At the same time, new jobs will be created in manufacturing, sales, supervising, servicing, and maintenance of these machines, which will require different set of skills than seasonal labor in farming, but will provide year-around quality jobs with better pay.

Many farm labor tasks are difficult, requiring heavy repetitive motions that pose substantial risks to the wellbeing of farm laborers. The advancements we have witnessed over the last decade in AI, robotics, and other relevant disciplines suggest the these technologies will reduce the physically demanding, risky, and hazardous tasks and create a better working environment for people involved in farming (e.g., remote operation and supervision using augmented reality).

As we move into smart farming of future, where farming decisions are made increasingly with the AI-powered systems and implemented in the field by robotic systems, integration of ground and aerial robots for decision support and collaborative field operations would be an important direction. For example, there have been new research efforts for integrating sensing and field operations using UASs and ground robots in understanding disease pressure and nutrient needs and applying certain chemicals to achieve desired outcomes. Similar technologies could be used to improve irrigation management in various specialty crops including nuts, grapes, and tree fruits.

Animal Agriculture

Dairy

Robots or automated systems currently used in the dairy industry include automatic milking systems (AMS), feeding systems, teat sprayers, calf feeders, hoofbaths, and manure handling among others. Clearly, the offerings and market competition of several commercial manufacturers driving these technologies have only helped to improve the technology and offerings to the market. The first commercially available milking robots were available in the early 1990s. Early adopters of AMS technology initially carried the burden of the steep learning curve associated with the automated process of milking a cow. Presently, advances in milking systems place the milking machine at the center of data capture related to milk production, nutrition, reproduction, and animal health. Expected performance of these AMS aims to resolve current demands (and possible future ones) that dairy producers and markets impose on the industry. Although AMS made milking cows faster and more efficient while maintaining optimal milk quality and minimizing disease, there are several well-known challenges in dairy production such as increased demands on traceability and transparency throughout the food chain (Lopez Benavides and

Paulrud 2018). Despite these challenges, there are an estimated 35,000 robotics milking systems currently in use globally (Salfer et al. 2019).

Initial attraction to AMS resulted from the lifestyle associated with it (i.e., milkers not bound to strict milking times) and giving producers the opportunity to focus attention on other farm-related processes or other income opportunities. The mindset of relegating all milking routine steps to the machine has in some cases also translated into neglect of some basic management practices associated with the hygiene of the barn environment and maintenance of the milking machine, which generally result in substandard milk quality parameters. Nevertheless, the majority of dairy producers using AMS manage these systems effectively, maximizing cow productivity without affecting animal welfare or milk quality. Small and large dairy herds have now the capacity to use AMS and manage them quite proficiently, as the knowledge and field technical support has grown considerably over the last few decades.

The obvious trend in interconnectedness of cow information and devices in the farm environment (known as precision dairy farming) will help drive the dairies of the future. Research is ongoing on devices that monitor gait and locomotion, rumination, and breathing, among others, which will overall help dairy farmers understand the complex dynamics of the milking environment and how it can be improved. As AMS use continues to rise and will likely become the norm in many parts of the world, some challenges still need to be overcome. Because of the need for cows to be milked voluntarily, there will be more attention paid to managing lameness (King et al. 2017), the physical conformation and placement of the udder and teats, and cow behavior (Hallen-Sandgren and Emanuelsen 2017). Initial concerns about cow behavior when switching from group to individual milking—such as decreased milk yield, urination, defecation, increased vocalization (Rushen, de Passillé, and Munksgaard 1999)—have most likely been resolved, as demonstrated by Jacobs and Siegford (2012), but other societal concerns and perceptions will still need to be clarified (Beaver et al. 2019). People in the dairy industry usually define animal welfare by good health, hence installations have been designed to maximize animal health and productivity. Monitoring of behavior and productivity has proven to be useful for the early detection of health problems, which helps to improve milk production and minimize animal welfare concerns (King et al. 2018).

The concept of animal welfare of cows housed indoors (e.g., free stall systems) will continue to be debated, mainly because of the divergence in understanding of what natural behavior and animal welfare means for a domesticated animal. For this reason, newer developments in AMS-type environments and housing must account for societal concerns and animal motivations, among others, to ensure they become common practice and accepted by consumers (Beaver, Ritter, and von Keyserlingk 2019).

Precision Livestock Farming (PLF)

Robotics in poultry and swine production is currently under development, and there is currently a fair amount of potential for automation within these animal systems, which is mainly focused on the feeding of animals, and the processing of products (meat and eggs). However, this section focuses on the automation and robotics that interact with the animals.

In the swine industry, automation and robotics the focus has been on animal breeding and gestation areas. A group in Germany has successfully tested an autonomous robot for dairy manure scraping in a loose housing gestating sow system (Ebertz, Krommweh, and Büscher 2019). While the researchers suggest some modifications, the robot cleaned the area and was able to successfully interact with the animals within the pen. Other robotic applications are either not autonomous or operate in the absence of animals. A "boar bot" is a widely used robotic application in swine industry. This is either a cart or a small vehicle that can hold a boar or its leash. The boar bot drives around animals for nose-to-nose contact during heat checking and breeding of sows. While this is not an autonomous vehicle, it shows the need for robotics within the swine production systems. Another type of robot that is commercially available includes a robot that runs on rails that distribute straw across the pens. This type of robotic automation is needed mainly in Europe, where providing material for enrichment is obligatory by the animal well-being legislation since 2003 (Bracke et al. 2006). While not interacting with the animals directly, autonomous robots for cleaning stalls prior to animals entering the building to ensure biosecurity between groups of animals are under development.

In poultry systems, robots are being investigated in the broiler industry and the buildings for layer hens housed on bedded floor. Robots are designed to pick up any eggs laid on the floor, monitor environmental conditions at the bird level, turn over the litter, and spray disinfectants. TIBOT Technologies suggests that robots placed on the floor encourages hens to use nesting boxes, therefore decreasing the number of eggs laid on the floor (TIBOT 2019). Octopus Poultry Safe is a larger robot that is designed to turn the litter, sanitize the environment, disinfect the building, and collect data on temperature, humidity, carbon dioxide, sound, and light (Poultry World 2019; Octopus Robotics 2019). Besides commercially available robots, there is research documenting the development of these types of robots. For example, Georgia Tech University has designed a robot that can autonomously pick-up eggs (Usher et al. 2017). Feed delivery systems are a commonplace in both poultry and swine facilities. There are new automations that allow for new production systems or improved performance. One example of such a system is by Metabolic Robotics in broiler facilities that control the time of the feeding, sounds and light. Feed efficiency is increased by 4% under this system (The Poultry Site 2018).

While robotics and automation improve the efficiency and the effectiveness of labor, these changes are faced with some challenges such as initial cost, animal-robot interactions, and changes associated with production. Changes in the production can be minor, such as using a cleaning robot in between groups of sows in a farrowing house, or a major rethinking of housing changes associated with electronic sow feeders.

Research is being conducted to determine the reaction of the birds to both aerial and ground robotics systems in the broiler industry (Parajuli et al. 2018; Parajuli et al. 2019). While these studies showed an increased reaction distance to aerial and ground robot systems compared to humans, these tests compared a novel experience of a mechanical object with a habitual experience of the human presence. Once birds become accustomed to the mechanical objects, the reaction distances are likely to change. Further development of robotic and aerial systems in poultry production may include options for estimating bird weight, identifying and reporting non-ambulatory birds, and possibly removing dead birds.

Use of robots in pig production is difficult because of the curious nature of pigs. However, the need for automation in the swine industry has become increasingly important with the public's pressure to eliminate gestation stalls. Several European countries and some states have banned extended confinement of pregnant sows in stalls (Anil et al. 2003). One long-term solution includes the use of electronic sow feeding systems. These systems use radio frequency identification (RFID) tags to identify animals so that the amount of feed can be controlled for individual animal. Electronic sow feeding (ESF) stations have been around since 1982 (Olsson et al. 1986) and are currently manufactured by several companies. The challenge with these systems is the complete change in production systems. However, with the current legislation and increasing public pressure, these systems are becoming more mainstream. In addition, as ESF systems become more common, additional automation is needed to ensure proper care of the animals. This includes the need to detect non-pregnant sows, weight or condition score changes, and the need to detect illness. Boar stations have been integrated into some of the ESF layouts. This allows for detection of open or non-pregnant sows. Scales are available in some ESF systems, and estimation of condition score from depth video/images has been reported by Condotta and colleagues (2019). Stavrakakis and colleagues (2015) and Condotta and colleagues (2019) suggest that determining walking patterns of normal and abnormal sows could be detected with a depth video.

Recent publications suggest that new concepts for automation in swine industry focus on the ability to monitor pigs to provide information about their growth and well-being. For example, several researchers have developed and tested methods for estimating weights of pigs (Condotta et. al 2018; Kashiha et al. 2014; Kongsro 2014; Pezzuolo et al. 2018; Shi, Teng, and Li 2016; Stajnko, Brus, and Hočevar 2008; Wang et al. 2008; Wongsriworaphon, Arnonkijpanich, and Pathumnakul 2015). This line of research suggests that estimating weight from depth or digital cameras is reasonable. However, the difficulty is the inability to track individual pigs over time. Therefore, currently these systems would either need to use an RFID system to track individual pigs or simply record a pen average.

Another example is use of automation systems to identify feeding behavior of individuals within a group pen (Adrion et al. 2018; Brown-Brandl, Jones, and Eigenberg 2016; Kapun, Adrion, and Gallmann. 2016; Maselyne et al. 2017). These researchers showed that feeding behavior at the feed trough can be monitored successfully and that this information may be useful in determining illness in pigs. Increasing the timely identification of individual pigs with potential illnesses within a commercial size pen of pigs would help producers pinpoint treatment of sick animals and prevent spread to the rest of the herd, improving animal well-being and ensuring the judicious use of antibiotics. The current downside of this system is the need for a RFID tag. The cost, labor to install, and labor to remove the tags at the slaughterhouse are three apparent issues. The less apparent issue is the decrease in value of the ear. Ears are currently marketed as dog toys in the United States, and by placing a hole on the ear its value is significantly decreased. The development of robotics and automation products for housed livestock, specifically pigs and poultry, continues to grow. This growth is being spurred by the public pressure for changes to improve animal well-being and decrease use of antibiotics, and the increasing difficulty in finding labor.

The field of ground and aerial robots for crop production and animal agriculture is a dynamic area which is advancing at a very fast pace. These recent publications provide a comprehensive list of additional robotic technologies under development (Fountas et al. 2020; Fue et al.2020; Martinez-Guanter et al. 2020; Ren et al. 2020; Tsolakis, Bechtsis, and Bochtis. 2019.; Vougioukas et al. 2020).

Enabling Factors for the Deployment and Adoption of Robots in Agriculture

Machine Vision and AI

Machine vision and AI technologies are key enabling technologies for the advancement of ground and aerial robots. When a ground or aerial robot passes through the field, or interacts with livestock, it uses machine vision and AI to identify key attributes of the crop and the livestock, respectively. AI is defined as the intelligence demonstrated by machines to understand their environments and take actions to maximize its success of achieving its goals (Russell and Norvig 2003). One of the pressing needs in plant based agriculture (row crops, vegetables and orchards) is to manage weeds (Westwood et al. 2018). Machine vision and AI technologies have the potential to manage herbicide resistant weeds using a suite of management strategies (e.g., mechanical weeding and targeted spot spraying) as there is a lack of new herbicide models. Autonomous weed control using ground and aerial robots could be the gateway to increased use of robotic systems on the farm (Westwood et al. 2018).

Early commercial applications of machine vision and AI technologies could be found (FarmWave https://wAww.farmwave.io/; BlueRiver: http://www.bluerivertechnology.com/) and more companies are beginning to enter this cutting edge domain of AI based agriculture. A significant limitation to several machine vision and AI tools is the need for publicly available robust image training data sets. Some of the first few publicly available image training datasets are DeepWeeds (https://github.com/AlexOlsen/DeepWeeds), Date fruit harvest (https://ieee-dataport.org/open-access/date-fruitdataset-automated-harvesting-and-visual-yield-estimation), and Sugar Beets (http://www.dis.uniroma1.it/~labrococo/fds/syntheticdatasets.html). Having access to more publicly available training image datasets will lead to advancing the intelligence and capabilities of ground and aerial robots.

Open source technologies play a key role in advancing machine vision and AI models. Google's TensorFlow (https://www.tensorflow.org/) is an excellent example of an open source tool that offers some of the most advanced machine learning and vision tools. Machine learning is a subset of AI which involves machines learning from experiences and data. Another important open source technology is the Robot Operating System (ROS) which is a software environment aimed at creating applications for robots (https://www.ros.org/). A ROS environment dedicated to developing robotic applications for agriculture is now available (http://wiki.ros.org/agriculture). Open source technologies are contributing to the advances in robotics research and enabling increased number of start-up companies to offer robotic solutions in agriculture.

Big Data and Cyber Infrastructure

Cyber infrastructure and improved data flow in agriculture offer tremendous opportunities that are diverse and extensive (National Academies 2018); yet, there are challenges from both social (sharing) as well as technical (size, capacity, interoperability) perspectives. Many of the issues are similar for operations completed by autonomous robots and for operations that include humans as control agents. Much of the enabling of improvements in logistics, efficacy, efficiency, and sustainable production stem from using the data itself, sometimes in near real time, sometimes in retrospective analytics (Buckmaster et al. 2018). Applications for big, shared, public data (often anonymized, but not always) include marketing, analytics for prescriptions and strategic yearly decisions, model building for predictive and preventative maintenance, and even tactical within-season decisions. Some of these application areas are most effective when data sets are an agglomeration across a region. A challenge in these (sharing) cases is convincingly communicating of the value (of sharing) to those who own the data to share.

For true mining of insights, the data must have the full backstory or context (metadata) associated with it (Evans, Terhorst, and Kang 2017; VanEs and Woodard 2017). At times, the definition of metadata and data gets blurred. For example, the speed of the planter might be "the data" to be interpreted since the decision and actions are control, path planning, or logistics of keeping the planter boxes filled; later, when trying to ascertain impacts of practices on production, speed of the planter would be metadata or context (as one of many variables which might have influenced yield). There is a wide variety of data that could be collected in cropping systems (Table 1). Those data elements have assorted resolutions in both space and time, highly varied accuracy levels and different origination points (several machines or sensor systems); this offers a wild frontier of opportunity for improvement in the design of data collection, storage, transfer, and access systems as well as improvement in decisions and actions on actual farms (Evans, Terhorst, and Kang 2017).

As explained in detail in the next section, connectivity is a key aspect of cyber infrastructure in automated and non-automated processes. In agricultural contexts, it is often the upload speed that is more limiting, because control files (download) are relatively small; but, the inputs needed by cloud computing algorithms are sometimes very large—particularly if those inputs are images or videos. For example, a typical UAS scouting flight for 20 minutes over a 100-acre field would generate a folder 4 GB in size, containing more than 400 color images plus video (400 ft flight elevation, images at 30 mm resolution, and with 75% overlap; J. Scott, personal communication). With only digital subscriber line (DSL) connectivity, it will take 20 to 30 times longer to upload the data than it took to generate it. "Real time" is a term that does need a bit of explanation in agricultural contexts. Some data (especially for control) must be within in milliseconds for safety and operations sake. Some data (such as bin or hopper status) could have a few seconds of latency without any significant impact. Some data (soil organic matter, soil temperature) is more for model and planning purposes, so latency of even a day(s) might be acceptable. Most importantly, the data regarding control must be local or have extremely high reliability and low latency. The assorted communication pathways (3G, 4G, 5G, Wi-Fi, LoRa, TV whitespace) can each play a role in data flow from remote devices, but no single pathway will serve as the universal economical solution.

The value of functional cyber infrastructure which raises the level of data-enabled decisions and actions comes from a blend of scouting and anomaly

Table 1. Some typical data elements for cropping systems as well as examples of value.

Data Element	Examples of Potential Value
Records of who/what/where/when	Critical context for later analytics on production and logistics
Imagery (RGB, NDVI, LiDAR, hyperspectral, thermal)	Scouting, anomaly detection, support analytics for treatment comparisons or correlation to other sensor data
Machine sensors (location, fuel consumption, battery status, slip, crop or soil moisture, speed, spray rate, rate)	Improved control of the machine functions, improved system logistics, metadata for analytics regarding seed practices
Soil sensors (moisture, temperature, chemical/biological attributes)	Improved logistics planning, influence on production activities, context for deeper analytics on other data

detection, estimation of differences due to treatment(s), estimation of yield, and improvement of logistics (including both autonomous and supporting non-autonomous operations (Evans, Terhorst, and Kang 2017). Much of the benefit can be obtained without sharing data, and that reduces risk (Department of Homeland Security 2018); however, some of the benefits of truly big data analytics and models (whether descriptive based on biological, chemical, or physical science fundamentals, or AI) do require data sharing to build datasets large enough to robustly capture effects.

Regardless of whether there is "public" sharing of data, there is always a need for interoperability. This is currently a dire need in both cropping and livestock systems. For example, sharing of simple information such as field boundaries can be problematic because of assorted formats, naming conventions, and compatibilities (but it should be seamless to share some information aggregated at this level by others such as the Farm Service Agency). Even with work such as that of AgGateway (www.aggateway.org) in the standardized precision ag data exchange (SPADE) project, we find that many agricultural firms are left with a data-driven dream rather than data-enabled reality. In the case of livestock systems, it is typical that feed characteristics and feeding records be in one system while data regarding production (milk, gain, etc.), activity loggers, and health (and treatments) are in other systems. Data regarding weather or other external factors (input and product pricing) are often public but require programming to automate consumption into decision tools.

Despite many diagrams to the contrary, data do not need to reside in a common cloud platform for systems to work well—in reality, that common repository will be rare. The reality is that machine data may be in an equipment company's cloud: weather may come from a public source, genetic information may reside in the seed company's service, and chemical application data may come from a service provider. Interoperability and substantial compatibility is needed so that these layers of information can be merged for insight generation (Buckmaster et al. 2018). This interoperability has layers of sharing and security protocols, data models, and file formats. Even when data are in a common cloud platform, the file interoperability issues exist. Interoperability is improving with published application program interfaces (APIs), but many of the APIs are non-standard and specific to the software, which is unwieldy due to the number of players. Other new developments in data models including geohash indexing and graph databases will also facilitate data movement and mining; the collaborative development of APIs and ontologies (relationships between knowledge representation) should yield huge benefits of improved compatibility. That collaborative development should and will be via open source efforts. Open source development has been the boon in internet development and adoption (Androutsellis-Thotokis et al. 2010). Open source is a paradigm and agreement that permits users to modify existing code or designs with enhancements or extensions. As it relates to data movement and compatibility (hence interoperability), open source drastically reduces the need for duplicative work. Solutions that work will get used, refined, and propagated. A prime example is the open publishing of APIs. Firms, of any size, that want their data to work with other data, will save tremendous amounts of time by using, studying, modifying, and distribution solutions that meet criteria from multiple perspectives. While open source software has been critical in countless disciplines and industries, it has been largely overlooked in agriculture to date. Fortunately, this is changing and the move toward more open collaboration will democratize data pipeline elements and result in platforms and data-centric solutions that work together better and are more widely available.

Farm Connectivity

Connectivity on farm can be thought of as enabling data generated on various machines and sensors to be shared among the sensors and machines, a farm network, and cloud-based storage and analysis systems. Wireless connectivity enables this data sharing to occur over significant distances at relatively low cost, because it does not require fixed hard-wired infrastructure. A common and simple example of such a system involves wireless moisture-sensor networks, which include sparsely installed soil-moisture sensors with wireless-transmission capability. Data can be transmitted by the sensors in either a passive or an active context. In an active system, the sensor nodes "self-report" the data they have collected to a remote computer system. In passive systems, the sensor nodes are queried through the network by the remote computer system, and they only report when queried.

Large commercial farms commonly apply water, fertilizer and crop protectants across whole fields in a non-differentiated way. If they use some form of precision agriculture, they typically use management zones that are multiple acres in size, because data are often spatially sparse and application equipment tends to be large, making more precise application impossible. If growers could obtain data at a higher resolution, square-meter areas in a field or potentially even about individual plants, then in the future they might be able to apply inputs in a highly targeted manner that is more economically and environmentally beneficial. Farm machines are increasingly collecting image and video data that require high transmission bandwidth, and new methods of data collection like remote sensing with drones require a large amount of storage, computation, and transmission bandwidth. Furthermore, cases exist in which post-harvest processing facilities could benefit from access to farm-collected data. At a cotton ginning facility, for example, the cost, timing, efficiency, and quality of processing seed cotton from farmers can be significantly enhanced if the facility has data on the incoming crop with sufficient lead time so that it can prepare to optimize onsite batching of varying seed cotton modules, staging and logistics, and charge appropriate processing fees. As a case in point, a cotton gin in southern Texas recently reported that their processing rate in the 2018–2019 ginning season dropped from 70 to 23 bales per hour when overly moist seed cotton modules were brought into the gin, costing more than $2,500 per hour in revenue (USDA-NASS 2019). Connectivity is thus critical for dissemination of farm data.

The type of wireless connectivity used depends on the needs of the particular device in the context of the given farm. The needs can be categorized in terms of bandwidth, range, and power requirements, not to mention cost. While wireless moisture-sensor networks typically have a low-bandwidth requirement, devices that collect images and video generate large volumes of data and require high bandwidth if near-term data delivery is needed. For example, Wi-Fi operates at 2.4 to 5.0 GHz and while bandwidth is large, it only has maximum range of roughly 100 m (Tzounis et al. 2017) in the best of circumstances, so it is largely not useful in the field. Many devices use cellular service, which operates at 3.0 to 5.0 GHz with high bandwidth of 2.0 Mbps to 1.0 Gbps, respectively. The range of cellular service is usually several km from the nearest tower, but many remote farm fields across the United States are well outside the range of cell towers. Satellite connections can be useful at locations where cellular service is unavailable, but the bandwidth is typically much lower and may not be suitable for rapid transmission of large data files. The long-range connectivity, known as LoRa, has range of many miles, but the bandwidth is low and it is suitable only for periodic transmission of small data files. A few other technologies are available but tend to have low bandwidth and low range.

Aside from bandwidth and range is the issue of standardization of data protocols so that devices and computing systems from different vendors are compatible. The machinery industry has worked together to develop the ISO 11783 (ISOBUS) standard that enables, for example, a tractor from one manufacturer to communicate with a planter from another manufacturer. However, compatibility among data-collection devices and cloud-based systems from different vendors is under development. Various standardization efforts, for example AgriRouter and DataConnect, are underway for this purpose.

The current state of wireless connectivity on the farm is that it is typically inadequate to move large data files in a timely manner, and even small data files cannot be transferred reliably with consistency. Many rural areas and particularly remote farm fields do not have wireless infrastructure, so data transmission is limited to small data packets at times when machines are in range of cell towers or farm-based networks. While 5G wireless technology is expanding, even to rural towns because, in part, of the USDA's Rural Broadband Initiative, the remoteness of a vast number of farm fields suggests that real-time data transmission as well as transmission of large data files like images collected with drones will be impractical for the foreseeable future (Wiegman, Pitla, and Shearer 2019). On the other hand, industry is developing standards to enable seamless utilization of farm data across vendors.

Interdisciplinary Agricultural Workforce

Various agricultural industries have installed local area networks (LAN) to monitor critical specialized systems. Equipment manufacturers such as John Deere, Case-IH, and AGCO would not even consider running their facilities without the IoT (Internet of Things—many devices connected together with sensors) technology that allows them to monitor, analyze and provide reports of their systems. Technicians assess equipment repair needs from the local dealerships and then make needed repairs based on electronic diagnosis of the issues on the farm. Grain companies such as ADM, Bartlett, Zen-Noh, and Cargill also use IoT technology to manage their grain handling systems. Ironically, the one entity that essentially feeds these corporations—the U.S. farmer—has used LAN and IoT technology at a much lower rate than a typical consumer to facilitate food production and food safety on their farms. Some IoT systems are deployed for irrigation systems, milking systems, swine facilities, and more, but these systems still require some technical expertise to operate. Many of these systems are such that the farm manager must travel to the location to make an adjustment to the system after an educated guess from the data allowed him / her to identify the issue(s) before the data was lost or animals / crops were negatively impacted to drought, disease or a number of other conditions.

These IoT systems will be an integral part of the ground / aerial robots that are moving into the agricultural production sector. These IoT systems will immediately require technical assistance and the typical IT technician will neither be ready nor want to work in a pig barn trying to determine why the IoT system is not performing. Hence, a new profession will emerge; individuals with a strong propensity toward quantitative systems thinking will be needed to perform the updates needed to IoT related systems that are used in the agricultural environment. There are examples of equipment manufacturers (e.g., Case IH, AGCO, and John Deere) offering autonomous concepts for field operations such as planting and spraying. The activities in this direction will necessitate a workforce inclusive of technicians who are adept at autonomous and electronic technologies. Local implement dealerships have hired a team of IT IoT professionals. Many have apps on their phone and the local farmer is expecting them to monitor their equipment. The expectation stems from the annual fees charged by companies for software and cloud services.

Moving forward, technicians to repair ground and aerial robots, the systems used to connect these robots to the cloud for real time (dynamic) review of the data, software development, and manage the remote updates will be needed. These technicians will not only need an understanding of the technologies used but also the environments in which these technologies are placed. The advent and popularity of video conferencing systems such as Zoom, Webex, GoTo meeting, and Skype systems will foster the adoption of IT personnel who spend more time working from home rather than working entirely from a business office. As society adopts these business and technology practices, the support system for IoT systems will both grow and become a leaned upon and needed support system. There are additional topics that the Farm IT professionals will need to address:

- Firewalls / security / privacy;
- The increase in data driven decision-making;
- The IoT system itself as the "manager"; and

- BYODx – the increase in Bring Your Own Digital eXperience;

The question then becomes how many people will be needed for managing IoT systems on the farm? What knowledge, skills, and abilities will they need to be effective? Moreover, how soon will they be needed? In the next decade, it is anticipated that there will be a 35% deficit of graduates with relevant education and experiential opportunities to fill science, technology, engineering, and mathematics (STEM) related jobs in agriculture and natural resources industry (Goeker et al. 2015). Engineering and technology play key roles in developing scientific tools of discovery and in developing methods to assist scientists working in agricultural sciences domain (NAE Grand Challenges for Engineering 2008). Providing interdisciplinary experiential learning opportunities to students in agricultural majors will be critical to address the demands of the future farm where use of robots could be a new normal. Although projects at the graduate program level provide opportunities for interdisciplinary training, current undergraduate agricultural science curriculums do not support intentional interdisciplinary training. Changes are required to traditional agricultural education curriculums to prepare workforce who will be working at the intersection of engineering/technology, and agricultural and food sciences in both academia and industry. Elements of robotics and automation, automated sensor data collection, cloud computing, wireless connectivity and IoT, and data science have to be embedded into undergraduate education curriculums of agriculture majors.

Liability, Security, and Data Privacy

Agricultural robots will bring new liability concerns to farmers. Who is liable if a farmer's robot causes injury to people or property? Liability and legitimate safety concerns are why small UAS (<50 lb) and UGVs (<500 lbs) will likely be the first autonomous systems widely commercialized. Traditional negligence cases require an injured party to prove *causation,* linking the careless act to the injury. When injury or damage results during autonomous robotic operation, lawyers for tort victims will cast blame in three places—the software developer (or manufacturer), the retailer, and the owner. These parties will blame each other in turn. This tension will make the contract license or lease for agricultural robots crucial to apportioning liability, since these agreements could exculpate the software developer even if a coding error caused the injury. Software license agreements may also include indemnity provisions that require the robot owner (farmer) to defend the robot manufacturer in the event of a negligence claim while under the farmer's control.

Security is another legal concern. The Department of Homeland Security has warned of potential problems arising from coding errors, delayed software patches, and hackers (Department of Homeland Security 2018). Disgruntled employees who work for robotic manufacturers are also a threat to security of these devices. An isolated incident may not be much cause for alarm, but concern multiplies when thousands of devices running the same software are all compromised at once. Designers and manufacturers must make sure robotic technology is built with the latest security measures, and that timely updates are provided to address new risks.

Finally, robotics manufacturers should not forget data privacy and ownership concerns. Robotic technology has the potential to generate enormous streams of data often linked to the manufacturer's cloud. When polled, farmers have expressed concern about what happens to their agricultural data privacy with new technology (Wall 2018). Similarly, many farmers have indicated that they do not understand the licensing agreements and privacy policies they are asked to sign when purchasing or leasing new ag technologies. Legally, the United States lacks a comprehensive data protection statute like the European Union's General Data Protection Regulation (GDPR), however, the industry has developed a private data transparency certification (www.agdata-transparent.com) that awards companies that clearly answer certain questions about storage, handling, sharing and disposal of the agriculture data they collect. There remains a need for clear, concise agreements and policies between technology providers and farmers.

Conclusions

- While labor challenges are driving the demand for automation and robotics in specialty crop production, optimal management of production inputs is a primary motivation for using ground and aerial robots in row-crop production.
- Use of UGVs in row-crop production has the potential to provide scale neutral technologies to producers with Farming-as-a-Service (FaaS) model. In a system where multiple small UGVs could be used in place of one high horsepower manned field equipment, adverse effects of soil compaction could be minimized. When multiple UGVs are used, even if one UGV is down for repair and maintenance, others in the fleet can still continue to do the operation thereby minimizing the risk of halting the entire operation.
- UASs are effective technology tools that are used in both row and specialty crop production for general scouting and special applications, respectively. High initial capital cost, limited flight time, and low payload capacity are limiting their widespread use. The UASs industry is advancing at a fast pace and is starting to offer systems that can handle heavy payloads with the ability perform material application (e.g., spraying).
- In animal agriculture, robotic milking stations are matured and commercially available, whereas, robotics in poultry and swine industry is still evolving. In addition to automating tasks in the animal barns, robots collect environmental and animal data that has the potential for early disease detection and improved animal welfare.
- There is a need for further research in assessing economic benefits of using ground and aerial robots in crop production. Interdisciplinary research efforts with teams consisting of engineers, agricultural economists, and technology companies are needed to fully understand the economic benefits of using agricultural robots.
- Autonomous farming using multi-pur-

pose robotic machines presents better economic viability than highly specialized machines, because then a large capital investment would not have to stay idle for a long time. Developing multi-purpose robots would, therefore, be another important aspect in the future to improve the viability of ground and aerial robots.

- High-speed network connectivity across rural America and data compatibility and inter-operability between systems are critical for adopting robotic and AI-based technologies to improve production efficiency.
- Converting data to actionable insights require full context or backstory of the data and the collection methods. Interoperability of datasets is key for seamless sharing of data among multiple stakeholders to generate useful information for decision making.
- Experiential learning opportunities in the areas of ground and aerial robots, IoT, and AI are currently missing in traditional agriculture education curriculums. Curriculums need to introduce these interdisciplinary experiential learning to train the next-generation agricultural work force. This will ensure that the work-force is prepared for the agricultural landscape of the future where it might be required for personnel to be competent in traditional agricultural sciences along with an understanding of how elements of mechatronics, data science, and AI interacts with crop, soils, and animals.
- Ground and aerial robots also provide an opportunity to attract new generation into farming, which, otherwise, is expected to face a crucial challenge in the future as the current generation of farmers retires.
- Deployment of ground and aerial robots in production agriculture could result in liability, security, and data privacy concerns. Industry is addressing data privacy concerns through programs such as data transparency certification, however more efforts are needed to address the liability and security concerns of ground and aerial robots.

Task Force Recommendations

- Farmers have always been reticent to adopt new technologies void of a proven ROI. Low adoption rates and narrow markets for these products require technology start-ups to rely on wider margin to remain economically viable. Researchers and technology companies need to work closely with the early adopters to quickly evaluate ROI of automated/robotic to support increased adoption of appropriate technologies.
- Rural high-speed broadband connectivity is essential for the successful deployment ground and aerial robots. Investments to support public-private partnerships for developing and building out innovative wireless IoT solutions are needed. Robust connectivity among autonomous systems will simplify exchange of information for efficient machine coordination while enabling data transfer to Edge and FOG computing hardware and remote computing infrastructure.
- Safety, operational, and performance standards must be developed in support of ground and aerial robot deployment in agricultural production environments. Standards are necessary to address product liability for both original equipment manufacturers (OEMs) and start-up companies. Standards also shorten product design cycles while ensuring the safe integration of ground and aerial robots to production environments.
- Educational institutions, government agencies and the private sector must initiate a dialog with policy makers regarding data privacy, security, ownership, and transparency in agriculture. These efforts will ensure open dialogue on ethical data use, and return of value for data generators and users. Perhaps it is time to consider HIPAA-like privacy rules for agriculture?
- The regulatory environment must keep pace with the changing landscape of agriculture to fully realize the expected benefits stemming from the deployment of ground and aerial robotic systems in crop and livestock production environments with reduced reliance on human labor.
- Robust educational programs are needed for updating policy makers on technology expansion in agriculture. It is essential for stakeholders, industry professionals and government agencies to remain abreast of recent developments in the private sector.

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