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Economics of agricultural robotics

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1 Introduction

The world is in the early stages of a wave of robotics in agriculture. As with previous waves of agricultural technology, farmers and agribusinesses are in the process of identifying which robotic technologies are worthwhile. The general objective of this chapter is to describe the economic potential for the widespread adoption of agricultural robotics worldwide including low- and middle-income countries. The study is of interest to farmers, agribusiness people, agricultural researchers, farm machine manufacturers, agricultural policy makers and members of the general public who have an interest in food security, the environment and rural economies.

For this chapter, the word 'robot' refers to a machine capable of autonomous operation without direct human intervention. The word robot tends to be used in the media and by the general public for any device capable of autonomous operation. Robots are often anthropomorphized as mobile and speaking but might take a wide variety of forms (e.g. stationary and mute). More technical discussions tend to use the terms like 'autonomous machine' or 'autonomous

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equipment', which are defined as mechanical and electrical devices that can perform certain functions without direct interaction with a human operator.

Innovations in agricultural technology have the potential to improve food security, food quality, and quantity of food produced, reduce the environmental footprint of agriculture, and help societies achieve food sovereignty goals, but in market economies, those technologies are only used if they have substantial benefits for farmers. In many cases, those on-farm benefits are mainly monetary but can include reduced workload, more flexible schedule, risk mitigation, quality and nutritional improvements, and enhanced farmer and farm family wellbeing. With every new wave of agricultural technology farmers and agribusinesses must sort out those technologies that help them solve their problems from those that solve the problems of others. Technologies may be introduced for a wide range of reasons. Researchers and technology developers often innovate to solve their understanding of the farmer's problems or to achieve their notions of public goods. Governments and non-governmental civil society organizations may advocate, subsidize and promote new technologies to achieve public goods that may or may not have farm-level advantages. Manufacturers and retailers usually introduce new technology to increase their profits. Farmers and agribusinesses use many sources of information to identify those technologies for the definitive test that is performance in on-farm use. Those sources include research results, the farm press, social media, participation in field days and farm shows, discussion with friends, family and neighbours, and government and non-governmental extension programs. It is the professional responsibility of agricultural economists, rural sociologists and other social scientists to provide information to help farmers, agribusiness and those who advise them to sort through the flood of new technology.

Agricultural work is often perceived as physically challenging drudgery. Consequently, 'automation' has been a goal from the earliest days of agriculture. Tools and machines were developed to make that work easier and more effective. The first steps of that process were manual (e.g. hoes, shovels and rakes). Subsequent steps included machines (e.g. ploughs, seeders and harrows) pulled by traction animals (e.g. horses, cattle, donkeys and camels) and more complex mechanical equipment powered by internal combustion engines (e.g. tractors and combined harvesters). In the future, mechanical equipment might be powered by electricity generated from wind and solar installations, hydrogen, methane or other renewable power sources.

Technology choice is a long-term interest of many of those who have studied the economics of agriculture at least as far back as the Physiocrats in Eighteenth Century France who compared the benefits of oxen and horses for tillage (Neill, 1948). There is a rich research literature analysing agricultural technology choices (e.g. Cochrane, 1958; Feder and Umali, 1993; Feder et al., 1985; Lee, 2005; Doss, 2006). Microeconomic theory has argued that the choice of production technology in any sector should be utility-maximizing (e.g. Henderson and Quandt, 1958), which farm management experts have agreed (e.g. Boehlje and Eidman, 1984; Kay et al., 2020). Choosing technology to maximize profit is usually the easiest analysis to implement, but utility theory indicates that there are many other factors (e.g. the value of leisure time, risk, capital and other resource constraints and transaction costs). While most new technology must at least cover costs to be widely adopted, in some cases those other sources of utility are more important than profit maximization in the choice among technologies that cover costs.

An important aspect of the study of agricultural technology has been documenting the patterns of technology adoption. One of the first studies of agricultural technology adoption was the work on hybrid maize in the USA by Grilliches (1957). Subsequently, there were adoption studies of tractors (e.g. Clarke, 1991), conservation tillage (e.g. Nelson, 1997) and many other technologies. The adoption of precision agriculture technology is relatively well documented. Lowenberg-DeBoer and Erickson (2019) review data on the adoption of precision agriculture (PA) technologies worldwide and show that some, such as Global Navigation Satellite Systems (GNSS), have been among the most rapidly adopted agricultural technologies in history, while others, such as variable rate technology for fertilizer, have lagged. Lowenberg-DeBoer (2019a) hypothesizes that economic benefits have been a good predictor of long-run adoption of PA technology, but the short-run adoption patterns are more difficult to predict because they depend on a multitude of factors including the education level of farmers, credit availability, marketing of the technology and social pressure in rural communities. Tey and Brindal (2022) did a meta-analysis of PA adoption studies and showed that economic benefits are the most reliable predictor of PA technology adoption.

The information gap addressed by this chapter is the lack of a good overview of the economics of agricultural robotics agriculture. Research and commercialization of agricultural robots has advanced rapidly since Lowenberg-DeBoer et al. (2019a) did their review of the economics of crop robots. Milking robots have been commercially available since 1992 and have been widely adopted in Northern Europe and other parts of the industrialized world, followed by robots for animal feeding, manure handling and intensive livestock tasks. Information on the economics of livestock robotics is scattered in numerous studies. The general objective is to describe the economic potential for the widespread adoption of agricultural robotics in agriculture worldwide including low- and middle-income countries. While robots can be used to collect information for advancing precision agriculture, the focus of this chapter is on the use of robots to accomplish physical farming tasks (e.g. seeding, pesticide application, fertilizer spreading and harvest). The specific objectives are as follows:

- Review the adoption history of robotic technology in agriculture;
- Summarize the benefits expected from agricultural robotics;
- Discuss the implications of robotics for the agricultural sector, especially in terms of farm structure, farmer skills and agricultural institutions;
- Identify the likely impact of robots in agriculture on the distribution of income and rural standards of living; and
- Summarize policy, regulation and institutional issues related to the adoption of robots in agriculture.

2 History of adoption of agricultural robotics

Multiyear use of a new technology is the best indicator that at least some farmers and agribusinesses have found the new technology to be beneficial. Even though the history of agricultural robotics is short, it can provide some insights into the economics and potential adoption patterns for the future. This section will provide a brief overview of the adoption of agricultural robotics by farmers and agribusinesses.

The context of the adoption of agricultural robotics is a long history of innovation by farmers, blacksmiths, engineers and scientists with the goal of producing more food with less human effort (Diamond, 1998; Smith and Marx, 1998; Tudge, 1999). In most cases, this innovation historically was driven by two forces: (1) the earth's resources are fixed, but the growing human population required more food and (2) developments in other human activities provided ideas and innovations that could be adapted for agricultural use. For example, the large workhorses that were a primary source of agricultural power before motorized mechanization were originally bred in the late Middle Ages for military use. With the development of crossbows and guns, knights needed heavier armour and consequently stronger horses were needed to carry that heavier armour. Only later did farmers realize that those large horses also enabled them to do more work in a day than the oxen, smaller horses and ponies that were previously used. The growth of manufacturing in the nineteenth century increased the demand for labour, led to the growth in wage rates and, as workers migrated to the cities, it made it hard to find agricultural workers. The steam and internal combustion engines developed for industrial purposes were adapted to make the remaining few better-paid farm workers more productive. Agricultural robotics is largely built on technologies developed for space and military use. For example, the ideas for GNSS grew out of the American space program and were developed by the US military before being released for civilian use. Similarly, UAVs and satellite remote sensing were first developed for military use. The motivation for adapting these technologies for agricultural use is familiar from earlier waves of agricultural innovation. Farmers needed to produce more food with fewer workers and fewer resources. But with agricultural robotics, the environmental motivation has become more urgent. Using fewer resources in production is not just cost savings but also a reduced environmental burden on the planet.

Table 1 lists selected milestones in agricultural robotics. The dates, countries and technologies listed are intended to be indicative of the general adoption patterns but will be discussed for years by technology historians. No technology springs fully developed from the laboratory or design studio to the farm. It is an iterative process with basic research opening new opportunities for technology development, applied research to show the potential for application of this new science, technology development that converts scientific ideas into usable commercial products and entrepreneurship that takes those potentially commercial technologies from the factory to the farm. Sometimes each step takes years, and there are many false starts along the way. In many cases, there are parallel developments in different countries and by several companies or research organizations. The list in Table 1 has attempted to list the first mover for each technology, but dating technology introduction is not always simple. It is not always clear when a technology moves from being a scientific discovery, to a prototype, to the beta test stage and from there to being a standardized commercial product.

2.1 Robotics in livestock production

The most common robotic technology in agriculture is milking robots, which allow cows to be milked without direct human involvement. Traditionally,

Table 1 Selected milestones in agricultural robotics

Year	Technology or activity	Company or Organization	Country	Reference
1983	Executive order that allowed civilian use of the Global Position System (GPS)	US government	USA	Brustein, 2014 Rip and Hasik, 2002
1983	UAV fertilizer and pesticide application	Yamaha	Japan	Sheetz, 2018
1992	Milking robot	Lely	Netherlands	Lely, 2022 Sharipov et al., 2021
2011	Weeding robot	Ecorobotix Naïo Technologies	Switzerland France	Ecorobotix, 2022 Naïo, 2022
2017	First fully autonomous field crop production	Harper Adams University	UK	Hands Free Hectare, 2018
2018	Autonomous chaser bin	Smart Ag	USA	Smart Ag, 2018
2022	Autonomous large scale tractors	John Deere	USA	John Deere, 2022

milking was done by hand. The conventional machine milking uses a vacuum technology that mimics a calf sucking but still requires a human operator to place the milk machine on the cow (or other dairy animal) and remove it when milking is completed. Because the udder shape differs slightly from animal to animal, attaching the milk machine and removing it could not be a simple mechanical process. Electronic tags (EID) allow a milking robot to access a database of udder coordinates for specific cows and place the milking equipment correctly (Knight, 2020). The adoption of milking robots is around 30% of dairy farms in Iceland and Sweden and more than 20% in countries, such as Belgium and the Netherlands. Adoption has been low in other major dairy countries, such as Canada and the United Kingdom (7%), the United States (3%) and Australia and New Zealand (less than 1%) (Eastwood and Renwick, 2020). Milking robots are on their way to becoming a widespread practice in industrialized countries for medium and larger dairy herds (i.e. >50 cows), but the transition will take time because of the infrastructure replacement cycle for milking facilities. For example, in France, only 10% of dairy farms used robot milking in 2018, but 70% expected to install robots when they replaced milking facilities (Lachia, 2018). Many of the milking systems are linked to automated feeding of varying amounts of concentrates to cows based on milk production (Ordolff, 2001). Other digital automated technologies in livestock agriculture include poultry feeding systems based on bird weight, egg counting and computerized control of ventilation based on temperature and humidity (Banhazi et al., 2012).

2.2 Autonomous crop machines

For decades, universities and research institutes have had prototype autonomous crop machines that were demonstrated on parking lots and football pitches. A few were even evaluated in the field for specific crop operations (Lowenberg-DeBoer et al., 2019a). Hands Free Hectare in 2017 marked a turning point because it was the first public demonstration of using autonomous crop machines throughout the growing season to produce and harvest commercial crops (Hands Free Hectare, 2018). In the last five years, major manufacturers of farm equipment have announced their autonomous machines (Table 1), and there are over 40 start-up companies around the world focused on developing commercial autonomous crop machines.

Because autonomous crop machines started to be commercialized very recently, data on their use is very limited. Weeding robots are being trialled all over Europe, but only in France has the approximate number of robots been made public. Lachia et al. (2019) estimated that there were 150 weeding robots used in 2018 in French agriculture, mainly for weeding organic vegetables and sugar beets. Similarly, in North America, various autonomous crop machines are starting to be commercialized, but quantitative estimates are rare. Erickson and Lowenberg-DeBoer et al. (2021) estimate that 4% of US agricultural input dealerships use robots for crop scouting services and 2% use them for providing weeding services. However, those dealers expect substantial growth by 2024 with 18% expecting to offer robotic crop scouting and 13% expecting to offer robotic weeding by that time. Crop scouting robots are used to gather very detailed information on plant conditions (e.g. weed infestation, insect populations, disease symptoms and nutrient deficiencies). They can be used in combination with remote sensing. The satellite or UAV images provide a general perspective. Robots are sometimes programmed to collect detailed data on anomalies (e.g. areas where crop growth is lagging) identified via remote sensing.

2.3 Uncrewed aerial vehicles

Uncrewed aerial vehicles (UAVs) are also called 'drones'. They are 'robots in the sky'. Like ground-based autonomous machines, UAVs have been a popular topic for agricultural researchers and in the farm media for the last few years. Most UAVs are used for information gathering and that information can increase input use efficiency, but they can also be used to accomplish physical tasks, in particular, to automate input application. In most cases, UAV input application is like map-based variable rate technology. Information gathering is a separate activity. The application map is created by a human operator. The UAV only delivers the input to the site. UAVs are especially useful for spot spraying pesticides or localized fertilizer application. Many industrialized countries regulate UAVs tightly because of concerns about spray drift and possible negative interactions with civil or military aviation. Consequently, UAV input application is often banned or highly regulated. For example, in the UK, UAV spraying herbicides is currently allowed only for applying herbicide to inaccessible locations under limited conditions. Switzerland has led Europe in allowing some more flexible testing of UAVs for input application (Lowenberg-DeBoer et al., 2021). The 2021 CropLife survey shows that 14% of US ag retailers provided UAV input application services that year. By 2024, 29% of those ag input dealers expect to offer UAV input application services (Erickson and Lowenberg-DeBoer, 2021). Anecdotal accounts indicate that UAV input application is quite common in some low- and middle-income countries such as China and Brazil. Kendall et al. (2022) provide survey data from the Hebei and Shandong regions in the North China Plain, which indicates that the only precision agriculture technology used by a substantial number of farmers in that area is UAV spraying. Many technical challenges remain with UAV spraying, especially pesticide drift (Carvalho et al., 2020; Wang et al., 2021).

While data is sparse, the adoption of agricultural robotics in middle-income countries with substantial mechanized agriculture sectors seems to follow the same pattern as adoption in higher-income countries. A few milking robots are being used in middle-income countries. The use of autonomous crop machines is just starting. One exception is the use of UAVs for input application. Because regulation of UAVs is less rigid in some middle-income countries (e.g. China and Brazil), there are indications that in those countries, there is a growing business in UAV spot spraying and site-specific seeding.

The adoption of agricultural robotics in non-mechanized agriculture anywhere in the world is negligible. This non-adoption is largely due to the fact that robotic technology from mechanized agriculture does not transfer easily to non-mechanized farms, and research to adapt the technology for smallholder farms is almost non-existent. No agricultural robotics have been developed and commercialized with the non-mechanized smallholder farmer in mind.

3 Expected benefits of agricultural robotics

Consideration of the expected benefits of agricultural robotics almost always starts with labour costs and labour availability but often quickly moves on to the benefits of greater precision in application, individualized management of animals and plants, more data which can be analysed to fine tune decision, selective harvest and other benefits not related to labour. In this section, an economic analysis of benefits will be presented for two technologies which have attracted the attention of economic researchers: robotic milking and autonomous crop machines.

3.1 Milking robots

Evidence of the monetary benefits of milking robots is mixed. Economic benefits can result from labour savings, up to around 18–30% in some studies, but around 10% on average (see Hansen, 2015), and increased milk production, perhaps of 10–15% per cow (Steeneveld et al., 2012; Hansen, 2015; Drach et al., 2017). Steeneveld et al. (2012), for example, quantified the capital cost of automated milking at €12.71 per 100 kg of milk instead of €10.10 per 100 kg of milk for conventional milking machine systems. However, Steeneveld et al. (2012) also found little difference between the economic performance of robotic milking and conventional systems.

In the long run, the data collected my milking robot systems may have a bigger impact on dairy farms than labour saving. That data can help better match feed and other cow management with individual animal requirements. It may also aid in the early detection of health issues. While labour required to operate robotic milking systems is minimal, human time and effort is needed to interpret the vast amounts of data collected in robotic milking systems. Farmers, as well as workers, can find themselves doing different work rather than less work (Bear and Holloway, 2019; Rose and Chilvers, 2018), and the stress of dealing with the vast quantity of data could negatively impact mental health (Hansen, 2015). The animal welfare implications caused by the changing relationship between stockman and cow (less contact between humans and animals) have also been explored (Butler and Holloway, 2015; Driessen and Heutinck, 2016); Holloway and Bear, 2019), although it is noted that data from robotic milking systems can be used to identify health and welfare issues with stock. The introduction of robotic milking has also been associated with the restructuring of national dairy systems with the total number of farms reduced and the remaining farms getting larger (Tse et al., 2017; Vik et al., 2019). Regardless of the relative efficacy of robotic milking versus conventional systems, the experience of changing farm workflows and structures after implementation provides a precedent for identifying some of the social, ethical and legal implications of robotic systems in arable farming.

The conclusion that emerges from the research is that while the profitability of robotic milking systems varies from farm to farm, overall, they are about a breakeven compared to conventional milking machines, which require a human to attach and remove the milker, but farmers adopted the systems for the more flexible work schedule and quality of life benefits (Straete et al., 2017; Bergman and Rabinowicz, 2013; Castro et al., 2015; Hansen, 2015). Dairy farmers particularly appreciated the ability to spend more time with family and in community activities when milking robots were used. It should be noted that until very recently, most milking robots were installed on medium-sized family run dairy farms (e.g. 100 to 300 cows). Often milking robots were installed as part of an intergenerational transfer on the farm. The younger generation was interested in dairy farming but not eager to take on milking cows two or three times per day for the rest of their working life. There are more recent anecdotal accounts of large 1000+ cow dairies installing robotic milking because of concerns about hired labour availability. The decision to use robotic milking may be quite different on those larger dairy farms.

3.2 Autonomous crop machines

The assessment of the economic benefits of autonomous crop machines often starts with labour saving and then extends to improving timeliness, greater accuracy of input application, reduced soil compaction when using smaller swarm robots and other benefits. Because autonomous crop machines are just starting to be commercialized, all the publicly available economic analysis is extrapolation from research results. Lowenberg-DeBoer et al. (2019) did a systematic review of published literature on the economics of autonomous crop machines. They found 18 studies covering arable and horticultural crops, mostly partial budgeting analyses of automation of one field operation (e.g.

seeding, weeding and harvesting). All those studies found autonomous crop machines to be economically feasible in certain circumstances.

Studies implementing whole farm analysis of the economics of autonomous crop machines have started to appear in the last few years. Shockley et al. (2019) developed a farm linear program analysis based on autonomous crop machine prototypes at the University of Kentucky in the USA. They show the economic feasibility of autonomous crop machines for American maize and soybean farms and highlight the potential for profitable use of autonomous crop machines on small- and medium-sized farms

Table 2 Summary of US whole farm[a] net returns from autonomous machines for maize and soybean cropping

Study	Scenario	USD change in net return[b] with autonomous machines
Shockley et al. (2019)	Baseline with planter, sprayer, N applicator autonomous[c]	−7155
	10% cost reduction	23 774
	7% yield increase	75 156
	Both a 10% cost reduction and a 7% yield increase with autonomous	106 085
Shockley et al. (2021)	Baseline of planter, sprayer, and N applicator autonomous with 100% human supervision[c]	−2399
	100% supervision with 10% cost reduction[d]	27 346
	100% supervision with 7% yield increase[d]	83 392
	100% supervision with 10% cost reduction and 7% yield increase with autonomous4	113 137
	Baseline with planter, sprayer, and N applicator autonomous and a speed limit of 3.2 km/hr[d].	−27 896
	Speed limit with 10% cost reduction[e]	1849
	Speed limit with a 7% yield increase[e]	57 501
	Speed limit with 10% cost reduction and 7% yield increase with autonomous[e]	87 246

[a] Both Shockley et al. studies assume an 850-ha farm in western Kentucky.
[b] For Shockley et al. (2019) and Shockley et al. (2022) Net Return is defined as gross revenue from crops minus seed, chemical, fertilizer and other variable costs, and machinery ownership and operation. Change is defined in comparison with conventional equipment with human operators.
[c] Planting is assumed to be no-till, so no-tillage operations. P and K fertilizer spreading, lime application and harvest are assumed to be done by a contractor. For estimates of increased net return, assume the autonomous retrofit cost from Shockley et al. (2022) (i.e. $13 148).
[d] The 100% human supervision scenario is to test the impact of legal requirements for 100% time human in-field supervision similar to California requirements.
[e] The 3.2 km/hr speed limit is to test the impact of speed limits similar to California requirements.

(Table 2). The analysis indicates that prototype autonomous machines for seeding, spraying and nitrogen fertilizer application are profitable if swarm robotics reduces cost by greater accuracy of input application or by reducing soil compaction.

Lowenberg-DeBoer et al. (2021) used the Hand Free Hectare (HFH) experience at Harper Adams University to estimate parameters for a linear programming analysis of autonomous crop equipment for arable farming in the UK West Midlands. They estimated cost curves (Fig. 1) that show autonomous equipment has the potential to reduce wheat production costs by US$18–US$37 per ton depending on farm size and flatten the cost curve by reducing the economies of size so that smaller-scale farms can come closer to the minimum costs of production. Estimated wheat production costs are reduced on all farm sizes. While net returns are positive for all farm sizes in the study, the return to operator labour, management and risk taking on the smallest UK farm considered is reduced by using the autonomous equipment because the reduction in hired labour cost does not cover the retrofit cost (Table 3). Operators of the smallest farm would be better off with autonomy if they had opportunities to use their time in other enterprises or non-farm activities. For the slightly larger farms, ROLMRT estimates are increased by autonomy. The analysis also shows that autonomy can cut equipment investment by more than half on larger farms by using smaller, low-cost equipment more intensively.

Lowenberg-DeBoer (2019b) used the HFH LP model to ask if autonomous grain carts were introduced into the UK, which farmers should be interested?

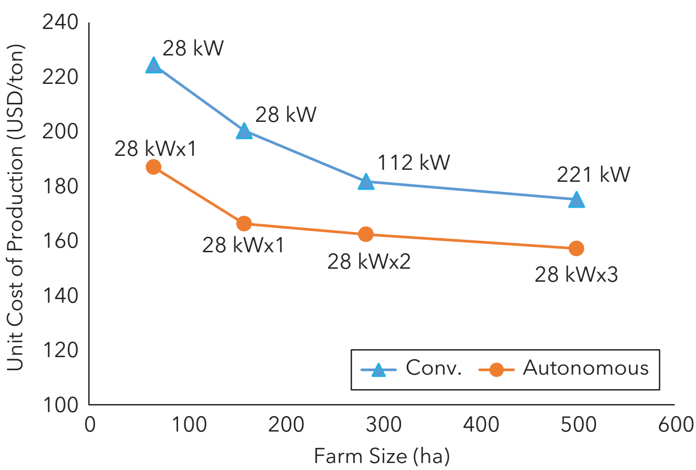

Figure 1 Estimated wheat cost of production in Britain with conventional equipment and retrofitted autonomous machines. The label at each node is the size of the tractor in the equipment set, and the number following the 'x' is the number of robot units used. Adapted from Lowenberg-DeBoer et al., 2021.

Table 3 Summary of UK whole farm economic studies of autonomous machines for wheat, barley and oilseed rape cropping

		USD[a] change in return to operator labour, management and risk taking with autonomous machines by farm size			
Study	Scenario	66 ha	159 ha	284 ha	500 ha
Lowenberg-DeBoer et al. (2021)	All crop machine operations autonomous	−4726	14 061	32 212	68 248
Al Amin et al. (2023)	10 ha triangular fields	−4729	14 525	37 604	94 325
	1 ha triangular fields	−3088	6740	25 661	75 122
Martian et al. (2023)	All Autonomous, 100% on-site supervision trouble free	−4726	-3034	14 998	33 883
	All Autonomous, 100% on-site supervision troublesome	−4726	−4395	7976	7212
	All Autonomous, remote supervision trouble free	−4726	13 400	31 031	64 786
	All Autonomous, remote supervision troublesome	−5667	−16 296	−13 392	−24 685

[a] Average exchange rate in 2018 from https://www.exchangerates.org.uk/USD-GBP-spot-exchange-rates-history-2018.html, USD/GBP = 0.7501. Change is defined in comparison with conventional equipment with human operators.

He found that with current wage rates, farmers are usually better off with human grain cart drivers if they can hire them reliably, but when labour availability is in doubt, the solution is to use the autonomous grain cart. In the UK, grain production harvest delays can lead to late seeding of subsequent winter crops and thus disrupt the entire farming system.

Al Amin et al. (2023) built on the earlier analysis for UK arable farms and showed that the swarm robot cost advantage is accentuated on farms with small and irregularly shaped fields (Table 3). With both 10 ha fields and smaller 1 ha fields, all farm sizes using autonomous equipment had lower wheat production costs than conventional farms. ROLMRT increased with autonomy on the three larger farms in the study (Table 3).

Because some countries and US states require on-site supervision of autonomous crop machines, Lowenberg-DeBoer et al. (2021) considered the economic impact of rules such as human supervision regulations. They found that in many cases when 100% time human supervision is required, the farmer is better off using conventional equipment. With current technology, if the human must be in the field, he or she can usually just as well drive the equipment.

Maritan et al. (2022) examined what human supervision of autonomous crop machines would be economically optimal if not required by law or regulation. That study shows that remote supervision (e.g. from the farm office) is optimal only if the autonomous operation is relatively trouble free (Table 3). They emphasize the need for greater robot artificial intelligence (AI) capacity so that the autonomous machine can resolve more issues without human intervention. Shockley et al. (2022) extended the earlier Kentucky analysis to consider the economic impact of autonomous machine speed restrictions. They find that for maize and soybean farms, autonomous crop machine speed restrictions like those in the US state of California (i.e. not over 3.2 kph) can make autonomous crop machines unprofitable (Table 2).

All of the crop robot economic studies cited have assumed that farmers own the robots as they have traditionally owned most conventional farm equipment. That assumption is used in preliminary studies because the economics of ownership are relatively simple; the farmer makes an initial investment and depreciates the robot's cost over several years. Robot rental, contracting and 'farming-as-a-service' approaches have potential advantages, but estimating the cost to farmer requires assumptions about the rate of return required by the company providing the service, market size, capacity utilization, the ownership of intellectual property developed by the robot AI and other business specifics.

Experience with the adoption of precision agriculture and other agricultural technology, and the economic analyses of crop robotics suggest that the adoption path may differ depending on the type of farming and the agricultural landscape. The economic case for autonomy is most compelling for horticulture because of the high-value crops and difficulties in hiring the seasonal manual labour required. Robots will probably be adopted quickly for seeding and weeding annual vegetables, but robotic harvesting of relatively delicate fruits and vegetables entails engineering challenges that are not easily solved. For arable crops, there will probably be two adoption pathways: (1) in those areas with large rectangular fields where motorized mechanization was very successful (e.g. US Midwest and Great Plains, Canadian Prairies, Brazilian Cerrados, Argentine Pampas and Australia), large-scale co-robotic smart equipment with some continuing on-site human operators is likely, (2) those areas with small, irregularly shaped fields (e.g. most of western Europe, eastern USA and much of Asia) where motorized mechanization was less successful are likely to choose small swarm robots, which, in some cases, will work without on-site human supervision. The ability of swarm robots to work efficiently in small, irregularly shaped fields gives them a major economic advantage in that topography, which may help farmers overcome the cost of transitioning to a very different way of organizing field work. The transition to swarm robotics would be facilitated if small, adaptable, low-cost robots could be mass produced.

There are several reasons why large-scale co-robotic smart equipment is likely to be used in areas with large, rectangular fields. A key reason is that swarm robotics reduce but do not eliminate economies of size. The cost of the hardware and software needed for autonomy is almost the same for any size of equipment. With large-scale equipment, some human operators are likely to remain in the field in a co-robotic arrangement because of the safety risks posed if large autonomous equipment malfunctions. Lastly, motorized mechanization in these areas is very successful, and it would probably be easier for most farmers to transition to large-scale co-robotic equipment than to switch to swarm robotics. The autonomous chaser bin (i.e. grain cart pulled by an autonomous tractor) is a good example of this type of co-robotic technology. A human operator in the combine harvester signals to the driverless autonomous chaser bin when unloading grain is required. That human operator is in the field and can stop the autonomous chaser bin if there is a malfunction.

Farm labour is increasingly difficult to hire almost everywhere in the world, including in developing countries. Rural young people in the developing world often see opportunities in the cities leaving farm work to children and their elders. Development of small, low-cost autonomous crop machines for use in small- and medium-scale farms has been proposed as part of the solution (e.g. Tarannum et al., 2015; Reddy et al., 2016; Valle and Kienzle, 2020; Al-Amin and Lowenberg-DeBoer, 2021), but unfortunately, no publicly available economic analysis has yet been done on the use of autonomous crop machines in the developing world. Setting aside for the moment the engineering challenges of developing low-cost autonomous crop machines and the entrepreneurial challenges of supplying them to farmers sustainably, the emerging literature on the economics of autonomous crop machines highlights some aspects of swarm crop robotics that would be of interest to developing country farmers including the following:

- Reducing human labour required for crop production with a modest equipment investment;
- Flattening the cost curve (Fig. 1) and reducing economies of size so that minimum production costs can be achieved at a smaller farm size than with conventional mechanization; and
- Ability to farm small irregularly shaped fields cost-effectively. This avoids the need to reshape rural landscapes and disrupt communities to create large rectangular fields on which conventional mechanization is most efficient.

4 Potential agricultural robotics in low- and middle-income countries

Most of the agricultural robotics adoption and economic analyses summarized so far in this report have been for mechanized agriculture in industrialized or middle-income countries, but to achieve the food security and environmental goals noted in the introduction, the use of agricultural robotics must reach smallholders in low- and middle-income countries, especially those on non-mechanized farms.

4.1 UAVs for smallholder farms

UAV services are being used by non-mechanized farmers in Asia and Africa, but the number of farmers and the area managed with UAVs is not well documented. Low-cost donor subsidized or venture capital-funded drone spraying is sometimes offered in developing countries, but at the current time, commercial services that cover all costs are often out of the range of small farmers (e.g. Njagi, 2019; Chikasha and Chipadza, 2021). In South Africa, there are even some doubts about whether larger mechanized farmers can afford UAV spraying (Daniel, 2021). It is possible that re-engineering to reduce costs, mass production and innovative business models can make these technologies more affordable for non-mechanized farmers.

There have been research interests and some business start-ups focused on supplying UAV spraying services on smallholder farms in Africa (e.g. Ayamga et al., 2021; Yawson and Frimpong-Wiafe, 2018). Unfortunately, robust data are not available on how widespread that practice is in the developing world.

For farms of any size, the advantages of UAV input application include targeting specific areas instead of spraying whole fields, application to fields too wet for equipment, application to inaccessible remote, steep areas and application in standing crops without damage to crops from equipment movement. For small holder farmers who would otherwise make pesticide application with a backpack sprayer, the use of a UAV potentially reduces pesticide exposure. However, there are many challenges to overcome in UAV input application including systems to refill spray tanks, fertilizer bins or seed hoppers, battery life, pesticide regulation label rates for spot application, training of users and drift to non-target areas (Carvalho et al., 2020). The profitability of UAV input application depends on the cost of the spraying service, effectiveness of the application given drift, input savings due to spot application, and improved yields because of reduced damage from the ground-based machines compared to alternatives (e.g. backpack sprayer, tractor-mounted or towed sprayer, fertilizer spreader or seeder, and application with crewed aircraft). Because smallholder farmers are unlikely to own UAVs, the cost of the UAV application service is crucial.

4.2 A vision for low-cost autonomous crop machines

For many researchers, research funders, entrepreneurs, politicians and venture capitalists, autonomous crop machines for smallholder farmers are an oxymoron. One of the main barriers to innovation in robotics for smallholders is cost. Autonomous machines are perceived as expensive. The development and spread of mobile phones provide a counter example. The first mobile phones introduced in the 1970s were heavy, clumsy and cost about US$3000. Many people imagined that they would always be a toy for the ultra rich. Now mobile phones are sold in shops and markets throughout the developing world, often for less than US$20. Technology improvement and high-volume manufacturing made the mobile phone much less expensive, and the prepaid business model fits the budgets and cashflow of many in the developing world. Mobile phones paved the way for the introduction of smart phones, which are increasingly used for PA apps. The combination of technology change, mass production and innovative business models could do the same for autonomous crop machines.

To develop practical agricultural tools that could achieve worldwide adoption, scientists, engineers and technology developers usually need a vision for the technology and design criteria. One vision is of a small wheeled autonomous crop machine with AI that could learn to seed, weed and harvest for the price of a motorbike. Some smallholder farm families in low-income countries have motorbikes, so that is a useful price point (US$500–US$1000) for an autonomous crop machine that could be widely adopted. While a leg robot might be useful in fields (i.e. it could step over obstacles), with current technology, leg robots usually cost several multiples of a wheeled robot of the same size. The ability of the autonomous crop machine to learn using AI would make mass production possible. Producing specialized robots for each crop and agro-ecology would be a high-cost low-volume business. A plausible business model is that a manufacturer delivers a generic autonomous machine which is taught what it needs to do (perhaps by working alongside a human). Appropriate tools for the autonomous machines would be adapted to the task. Some of those tools might be locally manufactured. The autonomous machine would be GNSS enabled to allow it to create maps (e.g. soil colour, soil strength based on the force required for hoeing and the yield from the plant-by-plant harvest). There are several possible energy sources for the autonomous machines (e.g. fuel cells, solar electricity and methane). To make use of the autonomous machines more affordable, especially initially when it is unfamiliar, rental or fee-for-service farm work might be implemented.

With the generic autonomous crop machine, many other types of digital automation become possible. For example, with a crop sensor, the autonomous machine might determine the fertilizer needs of individual plants and incorporate the required fertilizer in the soil at the base of each plant. This would be essentially what human farmers now do when microdosing fertilizer (Aune et al., 2017). To add soil capacity or yield goal information to this AI fertilizer decision process, the autonomous machine might use previously recorded soil, plant and yield maps. With robust and inexpensive sensors, the autonomous machine might also determine the presence of insects or plant

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diseases and apply insecticides or fungicides as needed. Weeds could be controlled mechanically or with targeted herbicide applications.

This vision of robotics for smallholder farmers represents an enormous engineering and entrepreneurial challenge, but it can be envisioned with current technology and may be facilitated by innovations. The millions of small farmers in the developing world should be an enticing market if someone could show businesses that there is a feasible technology and that there is a market. This would be a classic mass market business strategy as outlined by Prahalad (2004) in the book *Fortune at the Bottom of the Pyramid*. In agriculture, it would be similar to research, technology development and entrepreneurship that spread of hermetic grain storage through Africa and South Asia (Noughoheflin et al., 2017). Before the Purdue Improved Crop Storage (PICS) bag, manufacturers were reluctant to invest in grain storage innovations for small holder farmers because of the perceived lack of buying power. After PICS sold millions of bags in 30+ countries, there are many imitators and competitors.

5 Broader implications of agricultural robotics for the farm sector

Agricultural technologies often have economic and social implications that extend far beyond their farm-level benefits and costs. For example, motorized mechanization of agriculture often resulted in farm size expansion and rural depopulation, with the associated decline in rural political and economic influence. A more positive example is the introduction of hybrid maize in the USA resulted in the geographic expansion of the ‘Cornbelt’ to areas where the growing season was too short or summer rainfall too low for open-pollinated maize (Hart, 1986; Green et al., 2018). This was possible because hybridization gave breeders greater control over the maturity, drought tolerance and other agronomic characteristics of the crop. That expansion of the geographic area where maize could be grown in turn led to the growth of maize processing and intensive livestock production in those new maize production areas. Similarly, if low-cost agricultural robots like those described in Section 4 were developed and widely commercialized, the currently available research suggests that they could have major economic and social implications including the following:

- Impact of swarm robotics on farm structure – Small swarm robots can be almost constant returns to scale. With them, small farms can achieve the minimum cost of production, and larger farms can add more autonomous units that produce at that same minimum cost level. This would reduce economies of scale in agricultural production and eliminate one of the major motivations for farm size expansion. Whether the economics of size and scope in input purchasing, marketing, finance and other farm management functions continue to drive farm size increases probably depends as much on cultural factors, legal structures, and regulatory constraints, as on the production profitability. By rapidly adopting swarm robots, areas in middle- and low-income countries now dominated by manually operated smallholder farms or slightly larger farms using animal traction may avoid the social disruption of farm size expansion and rural depopulation. By reducing drudgery, increasing profitability and enhancing the image of agriculture as a high-tech industry, swarm robotics has the potential to help rural communities retain their young people and even attract talent from elsewhere.

- Ability to farm small irregularly shaped fields efficiently with swarm robots – In industrialized countries with a legacy of medium and small farms, motorized mechanization frequently led abandonment of small irregularly shaped fields or the transition to less intensive uses, such as rural residences or hobby farming. For example, this occurred in the eastern USA in the early twentieth century. Countries which tried to maintain a small farm structure were saddled with massive farm subsidy costs. This occurred in many European countries. The introduction of swarm robots may allow commercial agriculture to reclaim some of those abandoned small, irregularly shaped fields, which, in some cases, have other economic advantages, such as good soils, reliable rainfall and proximity to markets. Small farm subsidy programs may become less costly as swarm robotics helps reestablish profitability for agriculture in small, irregularly shaped fields. In areas dominated by manual smallholder farms or slightly larger animal traction-powered farms, conventional wisdom encourages motorized mechanization to deal with labour shortages and to improve productivity. Those areas may be able to skip the motorized mechanization step and move directly to robotics, avoiding the need to reshape the rural landscape into larger fields. This may also have environmental benefits in that small, irregularly shaped fields have greater biodiversity than large rectangular fields (Batáry et al., 2017; Fahrig et al., 2015; Flick et al., 2012; Firbank et al., 2008; Lindsay et al., 2013).
- The introduction of swarm robots could radically alter the farm equipment market structure – The core customers of the current group of major farm equipment manufacturers are a relatively small number of large farms. This leads to a ‘high touch’ marketing and service strategy for sophisticated products via intensive interaction with that relatively small group. In contrast, the swarm robotics vision outlined in Section 4 would require mass marketing of low-cost standardized products to millions of small- and medium-sized farmers. The optimal business model for this swarm robot market is not yet determined, but as with the prepaid business model used by mobile phone companies in low- and middle-income countries, it

may be quite different from the current business model. This change in the customer base and the business model may lead to changes in the farm equipment market structure. It will create opportunities for entrepreneurs who have the technical capacity to develop low cost, reliable autonomous machines and link that technology with innovative business models.

Of course not any of these outcomes are inevitable. They depend on many factors including the exact characteristics of the technology, the legal and regulatory frameworks, business decisions by major corporations and start-up companies, social media reactions and cultural attitudes about robotics in agriculture. Innovations using AI often depend on the reliable availability of high-speed internet access. Governments and civil society can encourage positive outcomes from agricultural robotics through digital infrastructure, appropriate legal and regulatory approaches, public sector research and education.

6 Social impact

The first question asked in most public discussions of agricultural robotics relates to the perception that this technology will eliminate many rural livelihoods, leading to farming communities with a few relatively wealthy farmers and many unemployed former farm workers who would either live in poverty or move to the cities. The loss of jobs to automation may occur most prominently in fruit and vegetable production where manual methods are still widely used, even in industrialized countries. However, because many industrialized countries have depended on migrant labour for fruit and vegetable production, this is not primarily a domestic problem for them, but rather a problem for the sending country. For industrialized countries, reduction in international migrant labour could help resolve political problems created by immigration and medical/biosecurity issues linked to international movement of workers during disease outbreaks. For the sending countries, the loss of migrant farm jobs is a mixed outcome because those migrant jobs were often not good jobs. They often did not pay particularly well. They often forced people to be away from their families for long periods. They often did not have health or social benefits. However, they were jobs and did provide incomes to people who often had few other options. Agricultural robotics will create a challenge in the low- and middle-income countries that depend on remittances from migrant farm workers to create other economic opportunities.

In the large-scale commercial arable farming sector, robotics is likely to mean many workers change their responsibilities, but unlikely to mean the loss of many jobs. In that sector, the major loss of jobs already occurred with motorized mechanization and chemical weed control. With the higher productivity linked to agricultural robotics, farm workers who adapt and retrain could achieve higher incomes and better standards of living. For example, a former tractor driver may supervise a swarm of autonomous crop machines or retrain to do robot training, maintenance or repairs. With the reduction in economies of size, some former farm workers may find entrepreneurial opportunities in small and medium robotic enterprises. From a social perspective, changing jobs, retraining, and adapting to automated working and entrepreneurship can be very stressful even in growing economies with a long-term demand for labour (Charlton et al., 2022).

For small- and medium-scale arable farms, robotics could create opportunities as well as challenges. Those farms could use robotics to lower their costs of production and be more economically competitive, but even with lower costs, their farm scale may not provide an acceptable standard of living. They could use the labour saved to expand farm size, find off farm employment or add farm enterprises.

In contrast to the widespread perception of the loss of jobs due to robotics in agriculture, there is the possibility of entrepreneurial opportunities created when the availability of human labour is no longer the binding constraint for agriculture. For example, one of the main constraints to organic or biodynamic farming in industrialized countries is the cost of labour. If organic growers could rely on autonomous weeding machines to control weeds and AI to identify plant diseases and suggest biological remedies, organic production could expand rapidly. In industrialized countries, many consumers would prefer to buy organic products, but they do not want to pay a premium. With robotics, organic production could undercut the costs of conventional methods and become the standard. Similarly, robotics could revive the production of nutrient-dense heirloom crops that were difficult to mechanize. For example, when maize production was mechanized, hybrids were developed with ears all at about the same height on the stalk to facilitate harvest; in the plant breeding process for harvest efficiency and other mechanization traits, nutritional and culinary diversity was lost. Autonomous machines with AI could be developed to harvest traditional maize varieties with ears at different heights. Similarly, the mechanization of tomato harvest required varieties that would ripen evenly. In the process of developing tomatoes for mechanical harvest and the other requirements of long-distance supply chains, nutritional and flavour were lost. Selective harvest with autonomous machines could allow commercial production of flavourful heirloom varieties. It could also create opportunities for the production of botanicals with valuable aromatic or medicinal properties, even though those crops require very intense management. Some of those entrepreneurial opportunities could be generated in low- and middle-income countries.

The common science fiction plot of robots replacing human workers and destroying livelihoods is not inevitable with the introduction of agricultural robotics. If low-cost, highly effective agricultural robotics becomes as ubiquitous as mobile phones in low- and middle-income countries are now, then with the enabling digital infrastructure, legal, regulatory and cultural environment, there is the potential for sustainable rural economic development based on intensive agriculture. Whether low- and middle-income countries gain or lose depends on how they manage the transition. Countries that build the physical, economic and social infrastructure for agricultural robotics stand to benefit. Countries that ignore the challenge may lose the low-wage manual agricultural employment that they now have, but not see the development of higher-wage agricultural opportunities with robotics. History suggests that the international community can help countries prepare, but it cannot oblige them to recognize the opportunity.

7 Policy, regulatory and institutional issues

Anticipating the issues that will arise with the introduction of new technology is very difficult because the future use of those innovations and the human reactions are not completely known. In general, people develop new uses for technology that are often far different from the intent of researchers or technology developers. For example, tractors were originally invented to replace draft animals for field work, but the availability of mobile mechanical power with rubber tires, hydraulics, electronics and power-take-off led to the development of unanticipated uses (e.g. direct seeding and conservation tillage, harvesting and packaging forage on-the-go and transporting crops to market). Regulations and standards need to be developed for the safe use of agricultural robots similar to the rules and guidelines for manufacturing automation and robotics. Some specific policy, regulatory and institutional issues that have been anticipated for agricultural robotics by researchers, farm equipment company staff, entrepreneurs, farmers and civil society include the following:

- Appropriate guidance on human supervision of autonomous crop machines – The EU and the US state of California currently require on-site human supervision of autonomous crop machines in most cases. Research shows that with current technology, the requirement of 100% time on-site human supervision of autonomous machines substantially cuts into the economic benefit of their use (Lowenberg-DeBoer et al., 2021). In many cases, if the human must be in the field, they may as well drive the equipment. Discussions are on-going about what should determine the level of human supervision. Maritan et al. (2022) show that the economically optimal supervision of autonomous crop machines in the absence of regulation depends largely on the frequency of human intervention required and on the placement of the supervisor (e.g. on-site or remote). Beyond the economic issues in supervision, health and safety concerns are often expressed, especially in relatively densely populated countrysides like those in most of Europe. In response to those concerns, the British Standards Institute (BSI) has organized an effort to create and autonomous agricultural machine code of practice for the UK. Factors that might influence appropriate supervision include the following:

- Size of the autonomous machine – Small swarm robots have less potential for causing harm than some of the large autonomous machines proposed by major farm equipment manufacturers.
- Speed of the autonomous machine – The state of California requires autonomous crop equipment to travel less than 3.2 kph. Under some ISO standards, autonomous machine categories are limited to less than 0.8 kph. Shockley et al. (2022) show that applying such speed limits generally in crop farming would undercut the economic benefit of autonomous machinery.
- Population of the countryside – A malfunctioning autonomous machine is less likely to create a health and safety problem in the sparsely settled Outback of Australia than it would in relatively densely populated rural areas in Great Britain.
- Site preparation – Signage, fencing and other site preparation might be used to prevent injury or death of workers, rural residents, companion animals, livestock and wildlife.
- Community preparation – Should rural communities near farms where autonomous machines are in use be notified? Who should be notified (e.g. everyone, those who sign up for the phone or internet-based alert system)? How should they be notified? Should they be notified only if the autonomous machines are working without on-site human supervision?
- Autonomous machine benefits beyond labour saving – For example, if the use of swarm robots reduces soil compaction, increases soil health and facilitates higher yields, then a higher level of human supervision can be economically justified.

- Training required for human supervisors of robots for both crops and livestock – What should the supervisors be on the alert for? How should they report incidents of human–robot interactions? This topic occupies a major portion of the Australian Autonomous Agricultural Machine Code of Practice (GPA et al., 2021).
- Agricultural robotics often requires internet access especially if AI is used – Internet access allows easy updating of software, reduces computational capacity needs by cloud computing and facilitates access to remote sensing and other public databases. Internet access in rural areas worldwide is often sparse and expensive, and it is particularly spotty in

low- and middle-income countries. Policies to encourage the development of rural digital infrastructure could include low-interest loans for rural internet providers and the formation of communications cooperatives that offer data services and subsidies.

- Data privacy and security – Agricultural robots would collect massive amounts of data on both crop and livestock farms. Some of that data may raise privacy issues for the farmer, farm family and others. Other data may be proprietary information for the farm or company. Rules need to be clear on who owns the data, who controls it, and how it is to be handled.
- Theft prevention – In countries where rural crime is common, the theft of small robots working alone in isolated fields is a frequently mentioned concern. Should robots have RFID locator chips implanted in them like pets and some domestic livestock are required to have in some countries? How should the resale market for used robots be regulated to make selling of stolen robots difficult?
- AI – While most of the agricultural robots currently in the commercialization pipeline have very little decision-making capacity, in the longer run, AI is an essential part of what will make agricultural robots useful. AI will allow robots to deal with many of the unexpected obstacles, thereby reducing human supervision needs. AI will help identify and target pests. Machine learning is an essential part of what will make AI useful, but it is also what makes it potentially dangerous because the manufacturer and human supervisor have little control over what it learns. There is also the question of who owns the knowledge generated by machine learning (e.g. manufacturer, farmer and the contractor supplying robot services).
- Technical training and retraining – Supervising agricultural robots, maintenance and repair of the machines and working with AI to resolve agronomic and livestock production problems are not in the skill set of most people in the agricultural sector today, especially on small farms in low-income countries. What training is needed to supervise agricultural robots? Should programs for robot training, maintenance and repair be started now, so that when the technology becomes common, there is a capacity to maintain and repair it? Should crop and livestock consultants be trained to use the data collected by robots and educated on how to interact with their AI systems?
- Public sector research and education – In the last two centuries, the basic scientific knowledge responsible for many agricultural advances has been developed and collected at universities and other public sector research organizations. Agricultural higher education is based on that scientific knowledge. Most robots in agriculture will probably be privately owned, by companies or individuals, and the data collected will be proprietary. In theory, if that farm data could be collected and analysed, it could lead

to unanticipated breakthroughs in crop and livestock production, with implications for food security, human health and safety, environmental management, biodiversity and other public concerns. Under what circumstances should public sector researchers have access to the agricultural data collected by privately owned agricultural robots?

- Policies to encourage agricultural robotics where it would have public good benefits – Some aspects of agricultural robotics have public good benefits (e.g. farming small and irregularly shaped fields with higher biodiversity, reducing pesticide use, avoiding the disruption of rural landscapes and communities to create large fields for efficient operation of motorized mechanization). Some of those public goods will be generated by private decisions given the right legal and regulatory guidance, but in some cases, it may be useful to encourage agricultural robot technologies. For example, where upfront investment and retraining transition costs are substantial, public subsidies might encourage farmers to re-equipment their farms with robots, instead of acquiring or continuing with motorized mechanization. The movement of agricultural research and educational institutions to the development and use of robots could be encouraged.

8 Conclusion

This report documents that robotics has been used successfully in agriculture for several decades (e.g. robotic milking), and technology is in the pipeline to make robotics ubiquitous on farms worldwide (e.g. mobile autonomous crop equipment). The discussion of benefits of agricultural robotics usually starts with reducing labour costs and coping with labour availability bottlenecks, but quickly moves on to other benefits, including greater food security, improving the quantity and quality of food production, increasing efficiency on small- and medium-sized farms, greater accuracy of input application, reduced soil compaction with small swarm robots, allowing field operations at times and places where they are difficult manually or with mechanical technology (e.g. wet soils, steep hillsides), profitable farming for small and irregularly shaped fields and automating the collection of crop and livestock data. By rethinking and re-engineering the underlying science, many of the benefits of agricultural robotics could be made available to medium and small farms in low- and middle-income countries. For example, the development of low-cost crop robots that could learn to seed, weed and harvest would help resolve labour constraints on manually operated smallholder farms and provide a basis for sensor-based fertilizer and pesticide application. If such low-cost, reliable and effective robots were developed and widely commercialized, it could radically change the farm sector. Numerous options exist to facilitate farmer access to robotic technology. Robots might be owned by farmers, rented or provided

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as an Uber-like service organized on a mobile phone app. The dominance of large-scale farms using motorized mechanical technology would diminish, and medium and small farms everywhere would have a greater possibility of success. Robotics has the potential to eliminate some manual farm worker livelihoods, and this is a specific problem for countries supplying migrant agricultural workers to more developed regions, but the technology also has the potential to create higher skilled, better paid employment in rural areas (e.g. supervising robots, training, maintenance and repair) and entrepreneurial opportunities. Realization of the potential benefits of agricultural robotics would require better digital infrastructure in rural areas, an appropriate legal and regulatory framework, facilitating digital entrepreneurship, retraining workers, revising technical educational curricula, attention to data security and policies to encourage agricultural robotics where it would have public good benefits.

9 Where to look for further information

Agricultural robotics and automation are changing rapidly as new technology is introduced and new business models are developed. Updating information on the economics of agricultural robotics and automation is an ongoing task. Beyond the scientific journals and other sources cited in the references, some sources which regularly have new information on this topic include:

- Future Farming (https://www.futurefarming.com/newsletter/) – The best single source of updates on commercial introduction of agricultural automation and robotic technology is the Future Farming newsletter. It also often has reports of farmer and agribusiness experience with the technologies.
- International Society of Precision Agriculture (ISPA – https://www.ispag.org/) – Conferences under the ISPA umbrella are often where new research on the economics of agricultural automation and robotics is reported. Those conferences include the International Conference on Precision Agriculture (ICPA) held in odd-numbered years and the European Conference on Precision Agriculture held in even-numbered years. Some papers and abstracts from the ICPA and ECPA can be accessed via the ISPA website. Many papers on the economics of agricultural automation and robotics are presented at ISPA-related conferences before they are published in the journals cited in this chapter.
- Global Institute for Agri-Tech Economics (GIATE – https://www.harper-adams.ac.uk/research/giate/) – GIATE annually organizes a symposium on agri-tech economics which attracts presentations on economics of agricultural automation and robotics work in progress. Papers and abstracts

from that symposium are posted on the GIATE website. In addition, GIATE posts articles, papers and presentations on agri-tech economics prepared by Harper Adams University staff.

- International Forum for Agricultural Robotics (French acronym is FIRA – https://www.agricultural-robotics.com/fira) – FIRA is organized by the Global Organization for Agricultural Robotics (GOFAR). It is a good source of information on the agricultural robotics industry. World FIRA, organized annually in Toulouse, France, attracts robot manufacturers, agricultural businesses, producers, investors, suppliers, entrepreneurs and researchers from all over the world. A North American focused event has been organized in California in recent years. Videos, reports and other information from the FIRA conferences are posted on their website.
- Grain Producers Australia (GPA – https://www.grainproducers.com.au/codeofpractice) – GPA and their collaborators introduced the first code of practice for autonomous agriculture machines. Updates are posted on the GPA site.
- British Standards Institute (BSI – https://knowledge.bsigroup.com/products/use-of-autonomous-mobile-machinery-in-agriculture-and-horticulture-code-of-practice?version=standard) – BSI has led the world in developing standards for autonomous crop machines for agriculture in densely populated rural areas. Updates on the BSI standards are found on the website.

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