Food and Agriculture Organization of the United Nations

Economics of adoption for digital automated technologies in agriculture

Background paper for
The State of Food and Agriculture 2022

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Abstract

The world is in the early stages of a wave of digital automation in agriculture. However, not all digital technologies are accessible nor worth investing by agricultural producers. This study investigates the appropriateness of a wide range of digital solutions, including in low- and middle-income countries, and, based on available evidence, summarizes the expected (social, economic and environmental) impacts of such technologies. The study further discusses the main drivers and barriers to adoption and the role of policies and regulations in creating an enabling environment.

This study finds that digital automation has already been successfully used in agriculture for several decades (e.g. robotic milking), with many more technologies in the pipeline (e.g. mobile autonomous equipment). Digital automation solutions can help reduce labour gaps, while generating new, skilled and entrepreneurial job opportunities; increase productivity and efficiency; and improve environmental sustainability and resilience. They can also be more easily adapted to local contexts (e.g. large- vs small-scale production; small, irregular and hilly fields vs large, rectangular fields).

However, realizing these benefits depends on the availability of appropriate digital infrastructure in rural areas, appropriate legal and regulatory frameworks, an enabling environment and on the digital and technical capacity of agricultural producers.

Acknowledgements

1   Introduction

The world is in the early stages of a wave of digital automation in agriculture. This technology wave includes growing use of robots in crops and livestock production, global navigation satellite systems (GNSS), on-the-go variable rate input application and operator assistance systems which optimize combine (and other machine) settings based on sensor output (see Annex 1). Digital automation goes beyond previous mechanical technology by automating some of the decision making as well as the physical work. As with previous waves of agricultural technology, farmers and agribusinesses are in the process of identifying which digital automation technologies are worthwhile. The general objective of this study is to describe the economic potential for widespread adoption of that technology worldwide including low- and middle-income countries. The study is of interest to farmers, agribusinesses, agricultural researchers, manufacturers, policymakers and the general public who have an interest in food security, the environment and rural livelihoods.

Innovations in agricultural technology have the potential to improve food security, reduce the environmental footprint of agriculture and help societies achieve food sovereignty goals. However, technology will only be adopted if they bring substantial benefits to farmers, including financial benefits but also reduced workload, increased flexibility in work schedules, risk mitigation and improved nutrition and wellbeing. With every new wave of agricultural technology, farmers and agribusinesses must differentiate between 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 farmers' problems or to achieve their notions of public good. Governments and non-governmental civil society organizations may advocate, subsidize and promote new technologies to achieve public goods, which may or may not advantage farmers. Manufacturers and retailers usually introduce new technologies to increase their profits. Farmers and agribusinesses use many sources of information – research, press and social media, field days and farm show, (governmental and non-governmental) extension programmes and discussions with friends, family and neighbours – to identify and test the performance of technologies on the farm. It is the professional responsibility of agricultural economists, rural sociologists and other social scientists to provide information to help farmers, agribusinesses 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 work easier and more effective. The first step of that process were manual tools (e.g. hoes, shovels, rakes). Subsequent steps included machines (e.g. ploughs, seeders, harrows) pulled by traction animals (e.g. horses, cattle, donkeys, camels) and more complex mechanical equipment powered by internal combustion engines (e.g. tractors, combine harvester). In the future, that mechanical equipment might be powered by electricity generated from wind and solar installations, hydrogen, methane or other renewable power sources. For the purpose of this study, agricultural automation can be defined as a general technology category in which human physical work and human decision-making are substituted for machinery and equipment to perform agricultural operations, reduce or eliminate human direct intervention and improve their precision.

Sensors, computers and other electronic technology created the possibility of automating some agricultural decisions, as well as the physical work of tilling soil, sowing seeds, removing weeds

and harvesting. In farming beyond the gardening scale, mundane decisions such as sowing depth by soil texture, distinguishing between weeds and crop plants, and selective harvesting of mature products, can become a special kind of drudgery. With computerization came the vision of making agriculture more site-specific instead of implementing one-size-fits-all crop management. This vision was labelled precision agriculture. A similar vision of making livestock management more specific to individual animals was labelled precision livestock farming. In the earliest stages of precision agriculture, computers and sensors were often used to collect data, which was then analysed by a human manager who would create a prescription map or other instructions for human operators or machines. But from the beginning the idea of on-the-go decision-making by computer algorithms was part of the vision (Mulla and Khosla, 2016). Initially that decision-making was by deterministic algorithms using programmed decision rules but, in the future, those decisions will incorporate learning from data collected by the machine via artificial intelligence (AI; see Annex 1). This study focuses on agricultural digital automation technologies that both automate physical work and some of the decision-making.

Technology choice is a long-term interest to those who studied agricultural economics as far back as eighteenth century France, who compared the benefits of oxen and horses for tillage (Neill, 1948). There is a rich literature analysing agricultural technology choices (Cochrane, 1958; Doss, 2006; Feder, Just and Zilberman, 1985; Feder and Umali, 1993; Lee, 2005). Microeconomic theory has argued that the choice of production technology in any sector should be utility maximizing (Henderson and Quandt, 1958), and farm management experts have agreed (Boehlje and Eidman, 1984; Kay, Edwards and Duffy, 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. value of leisure time, risk, capital and other resource constraints, transactions 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.

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 by Grilliches (1957). Subsequently, there were adoption studies of tractors (Clarke, 1991), conservation tillage (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 technologies 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 (VRT) for fertilizer, have lagged. Lowenberg-DeBoer (2018) argues that economic benefits have been a good predictor of long run adoption of PA technology, but in the shorter run adoption patterns are more difficult to predict because they depend on a multitude of factors including 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 precision agriculture adoption studies and showed that economic benefits are the most reliable predictor. Adoption of digital automated agricultural technologies other than those that are categorized as precision agriculture (e.g. GNSS, VRT) are relatively recently introduced and only sparsely documented.

The information gap addressed by this study is the lack of a comprehensive overview of the economics of adoption of digital automated technologies in agriculture. While there are good reviews of the economics of some aspects of digital automated technologies (e.g. precision agriculture), most are either outdated, are now starting as technologies enter the market (e.g. for crop robotics, targeted pesticide application) or are non-existent (e.g. AI for adjusting

combine harvester settings). The general objective is to describe the economic potential for widespread adoption of digital automation technology in agriculture worldwide. The specific objectives are:

- Review the adoption history of digital automated technology in agriculture.

- Summarize the expected benefits from digital automated technology in agriculture, the experience of researchers in predicting those benefits and the link between adoption and estimated benefits.

- Provide examples of the potential for adoption of digital automated technology using country examples that highlight what would be adopted, where and when.

- Discuss the implications of digital automated technology for the agricultural sector, especially in terms of farm structure, farmer skills and agricultural institutions.

- Identify the likely impact of digital automated technologies in agriculture for distribution of income and rural standards of living.

- Summarize policy, regulation and institutional issues related to the adoption of digital automated technology in agriculture.

2 History of adoption of digital automated technologies in agriculture

Multiyear use of a new technology is the best indicator that at least some farmers and agribusinesses have found it to be beneficial. Even though computerization of agriculture is relatively recent and the history of digital automation in agriculture even shorter, it can provide some insights on the economics and potential adoption patterns for the future. This section will provide a brief overview of adoption of digital automated technologies by farmers and agribusinesses.

There 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, two forces have driven this innovation: the fact that the Earth's resources are fixed but a growing human population requires more food, and developments in other human activities, which provided ideas and innovations able to be adapted for agricultural use. For example, the large workhorses that were the main source of agricultural power before motorized mechanization were originally bred in the late middle age for military use. With the development of crossbows and guns, knights needed heavier armour and consequently stronger horses to carry it. 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 they previously used. The growth of manufacturing in the nineteenth century increased the demand for labour, increased wage rates and, as workers migrated to the cities, made it harder 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.

Digital automation in agriculture is largely built on technologies developed for space and military use. For example, the ideas for GNSS grew out of the space programme of the United States of America and were developed by the military before being released for civilian use. Similarly, uncrewed aerial vehicles (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, namely that farmers needed to produce more food with fewer workers and less resources. However, with digital automation the environmental motivation has become more urgent. Using fewer resources in production is not just cost saving, but also reduces the environmental burden on the planet.

Because data on the use of digital automation technologies in agriculture is sparse, it provides at best an impressionistic view of adoption patterns. No country or international organization systematically collects data on the use of digital automated technologies in agriculture. There are a few precision agriculture adoption studies using standard sample survey methods (e.g. Australia, Denmark, United Kingdom of Great Britain and Northern Ireland and the United States of America) and many studies of a broader range of technologies using less robust methods (e.g. internet surveys, interviews with participants in farm machinery shows, data collected for marketing purposes). Understanding of digital automated technologies in agriculture must be developed by using this data in the same way that an art lover would view an impressionistic painting. Up close, the impressionistic painting is a collection of dots. From some distance, taking in the whole painting, those dots form patterns. Similarly, any individual adoption survey is of limited value because of the technology and country specifics involved. It is only when they are considered as a whole that patterns emerge.

Table 1.   Selected milestones in digital automation in agriculture

Year	Technology or activity	Company or organization	Country	Reference
1974	Electronic ID for livestock	Montana State University	United States of America	Hanton and Leach (1981)
1983	Executive order that allowed civilian use of GPS	United States of America government	United States of America	Brustein (2014) Rip and Hasik (2002)
1983	UAV fertilizer and pesticide application	Yamaha	Japan	Sheets (2018)
1987	Computer-controlled VRT fertilizer	Soil Teq	United States of America	Mulla and Khosla (2016)
1992	Milking robot	Lely	Netherlands	Lely (2022) Sharipov *et al.* (2021)
1997	GNSS agriculture equipment guidance	Beeline	Australia	Rural Retailer (2002)
1997	Nitrogen sensor	Yara	Norway	Reusch (1997)
2006	Automated sprayer boom section controllers	Trimble	United States of America	Trimble (2006)
2009	Planter row shutoffs	Ag Leader	United States of America	Ag Leader (2018)
2011	Weeding robot	Ecorobotix Naïo Technologies	Switzerland France	Ecorobotix (2022) Naïo Technologies (undated)
2013	Combine harvester operator assistance system	Claas	Germany	Claas (2022)
2017	First fully autonomous field crop production	Harper Adams University	United Kingdom of Great Britain and Northern Ireland	Hands Free Hectare (2018)
2018	Autonomous chaser bin	Smart Ag	United States of America	Smart Ag, (2018)
2022	Autonomous large-scale tractors	John Deere	United States of America	John Deere (2022)

Source: Author's own elaboration.

Table 1 lists selected milestones in digital automation in agriculture. The dates, countries and technologies listed are intended to be indicative of 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 commercially product.

2.1 Digital automation of livestock production

Digital automation of livestock farming requires identifying individual animals. From time immemorial, farmers identified their animals by colour, shape of the head and body, sound and other physical characteristics. In the late sixteenth century metal ear tags were developed, but still required a human to read them and act on the information. A radio frequency identification (RFID) system for cattle was developed in the 1970s. Initially, the RFID technology was in the form of a glass bolus placed in the rumen. In the early 1980s an implantable chip technology was created (Hanton and Leach, 1981). Governments in some industrialized countries now require electronic identification (EID) of cattle, sheep and some livestock, mainly for disease control purposes.

Several precision livestock technologies have been developed which facilitated management of individual animals based on EID. The most common digital automated technology in agriculture is milking robots, which allow cows to be milked without direct human involvement. Traditionally, 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 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. EID allowed a milking robot to access a database of udder coordinates for specific cows (Knight, 2020). Milking robots have been adopted by around 30 percent of dairy farms in Iceland and Sweden and more than 20 percent of those in countries such as Belgium and the Netherlands. Adoption has been lower in other major dairy countries, such as Canada and the United Kingdom of Great Britain and Northern Ireland (7 percent), the United States of America (3 percent), and Australia and New Zealand (less than 1 percent) (Eastwood and Renwick, 2020). Many of the milking systems are linked to automated feeding varying amounts of concentrates to cows based on milk production (Ordolff, 2001). Other digital automated technology 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 Global navigation satellite systems is key for digital automation of crops

Because plants are not self-mobile, digital automation of crop production is possible if the location of a block of plants or individual plants is known. In this sense, GNSS was an essential precursor to digital automation of crop agriculture. The development of the Global Positioning System (GPS) but the United States of America is listed in Table 1 because it is the first such system that was made available for civilian use. Other countries subsequently made their system available, including the European Galileo system, which went live in 2016, the Russian Global Navigation Satellite System (Russian acronum: GLONASS) which was declared fully operational in 1993, and the Chinese Beidou system, which was completed in 2020. Lowenberg-

DeBoer and Erickson (2019) document that GNSS guidance is widely adopted in most industrialized countries and is in the process of becoming standard practice in mechanized agriculture worldwide.

Figure 1. Percentage of American agricultural input dealerships using GNSS between 2000 and 2017
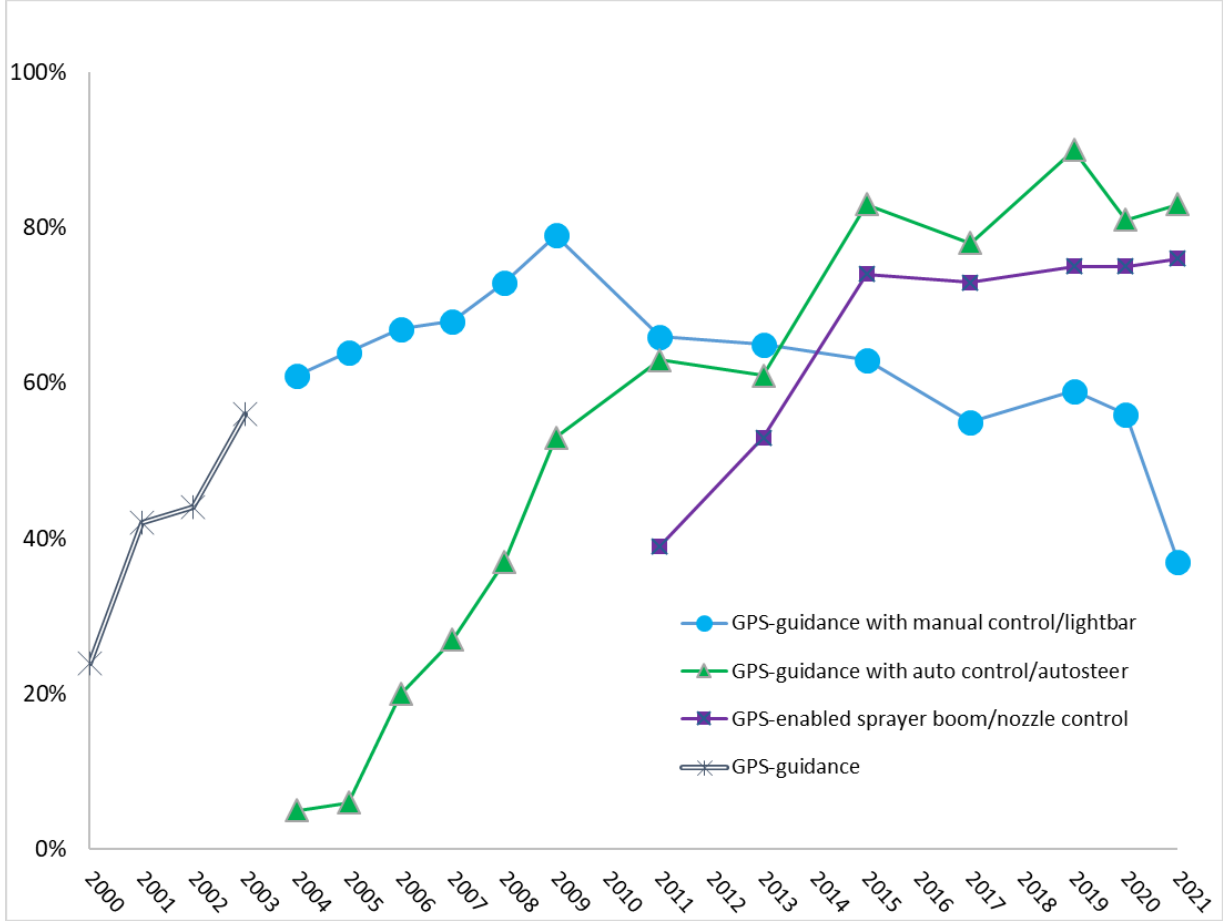
Notes: GPS-guidance refers to manual GNSS guidance before introduction of autosteer. GPS-guidance with auto control/autosteer was introduced on the American market around 2003, following the GPS-guidance with manual control/lightbar. Finally, GPS-enabled sprayer boom/nozzle control is for more targeted pesticide application.

Source: Adapted from Erickson, B. & Lowenberg-DeBoer, J. 2021. *2021 Precision Agriculture Dealership Survey Confirms A Data Driven Market For Retailers*. www.croplife.com/precision/2021-precision-agriculture-dealership-survey-confirms-a-data-driven-market-for-retailers/#slide=87709-87729-3

The rapid adoption of GNSS guidance in agriculture is exemplified in Figure 1, using the case of the United States of America. The figure is based on a survey by CropLife-Purdue Precision Agriculture, and was done with some of the same questions and a consistent methodology annually or biannually since the late 1990s; consequently, it provides a good perspective on precision agriculture technology trends. While this data is for dealerships and not farmers, it is highly relevant to the situation of the United States of America because many American farmers access precision agriculture as a service provided by cooperatives and fertilizer retailers. The use of GNSS guidance by dealers is similar to the use of that technology by their famer customers. Note that, prior to 2003, only GNSS manual guidance (i.e. lightbars) were available commercially in the United States of America. They were introduced in Northern America in the late 1990s. When the question about guidance was first asked on the CropLife-Purdue survey

in 2000, 24 percent of dealers were already using the technology. Manual GNSS guidance use by dealers peaked in 2009 at 79 percent. Since then, it has been replaced by autosteer which has now almost completely taken over steering. Autosteer requires a greater investment than manual GNSS guidance, but it is preferred when opportunity cost of capital is low as it is more precise and requires less effort from the human driver. In recent years, 80–90 percent of dealers have been using GNSS autosteer. The estimate varies slightly from year to year due to sampling variation. Combining all dealers that use some kind of GNSS guidance (manual or autosteer) the total is well over 90 percent. In terms of digital automation, what GNSS guidance initially did for the dealers was to help in steering tractors, fertilizer applicators and pesticide sprayers.

Technology is coming onto the market, taking the GNSS role a few steps further, by allowing the user to control input application more precisely. This includes sprayer boom control and nozzle control, which controls which areas are sprayed. It avoids applications on waterways, field paths, grass headlands and other non-crop areas. It also reduces double spraying of headlands. Sprayer boom control was commercially launched in 2006. By 2011, when the question was first asked on the CropLife-Purdue survey, 38 percent of dealers were using the technology. Use of sprayer boom control has risen to about 75 percent of dealers, following an adoption path similar to that of GNSS guidance. Seeder row shutoffs are a similar technology, which are mostly used to avoid seeding on non-crop areas and double seeding of end rows. Seeder row shutoffs are seldom used by American agricultural dealers because they do not usually provide seeding services, but are used directly by farmers. Anecdotal evidence suggests that seed row shutoffs are following a similar adoption path among American farmers.

While worldwide precision agriculture technology in general and GNSS guidance in particular was first used by larger farms (Lowenberg-DeBoer and Erickson, 2019), evidence from the United States Department of Agriculture (USDA) suggests that GNSS guidance is being used on American field crop farms of all sizes (Schimmelpfennig and Lowenberg-DeBoer, 2021). For example, GNSS guidance was used by over 80 percent of the largest farms in the USDA 2017 survey of winter wheat growers and 18 percent of the smallest farms. Similarly, GNSS guidance was used by 78 percent of the largest corn farms in the 2016 USDA survey and 9 percent of the smallest farms. In the United States of America, the lag in GNSS guidance adoption on the smaller farms is hypothesized to be linked to equipment replacement patterns. Smaller farms often buy used equipment. Consequently, when new technology is introduced in new equipment, it takes a few years before that technology is on the used equipment market.

2.3   Variable rate technology for input application

As civilian GPS equipment started to become available in the mid-1980s, research using it to guide agricultural input application started. The variable rate fertilizer field trials using Soil Teq (see Table 1) equipment in Washington, United States of America in 1987 is a good example. By the mid-1990s, some innovative farm cooperatives and American agricultural input dealers were offering variable rate fertilizer as a service for farmers (Akridge and Whipker, 1996, 1997; Lowenberg-DeBoer and Aghib, 1999). Commercialization of VRT applications started in Australia and Europe around the same time. Farmer adoption of map-based VRT has disappointed precision agriculture researchers and the companies commercializing the technology. With the exception of a few niches (e.g. VRT nitrogen on sugar beets in the states of Minnesota and North Dakota, United States of America), VRT fertilizer adoption is, on average, rarely over 20 percent of farmers or planted area anywhere in the world (Lowenberg-DeBoer and Erickson, 2019).

Thousands of research trials around the world and economic analysis based on those trials suggests that the main reason for the modest adoption of VRT fertilizer is lack of consistent profitability (Lowenberg-DeBoer, 2018). Trials often show mixed economic results. VRT fertilizer is profitable for some seasons and some crops, but result in losses in other cases. Map-based VRT is at an economic disadvantage compared to sensor-based VRT, as the underlying soil information is quite costly. This is partially due to it typically being based on manual soil sampling and laboratory analysis, and partially because it requires a separate step, in which an agronomist creates a prescription map. This human step is costly, slows down the process and can result in errors. Another reason for modest adoption of VRT is that the cost of misapplication (usually over application) is low. It is quite difficult to track excessive fertilizer application to a specific farm or field and, worldwide, very few jurisdictions attempt to make individual farmers and agribusinesses legally responsible for the subsequent environmental damage.

However, the VRT fertilizer systems developed in the 1980s and commercialized in the early 1990s were automated only in the sense that fertilizer application was controlled by GNSS and an agronomist-created recommendation map. On-the-go systems in which fertilizer application was changed based on sensor readings in the field were developed in the mid-1990s (Reusch, 1997) and first commercialized for nitrogen application by the YARA company based in Norway (see Table 1). By the early 2000s, there were several companies in Europe and Northern America offering similar on-the-go nitrogen variable rate application systems. In spite of widespread publicity in the farm media, intensive extension efforts in some countries and subsidies, adoption of the sensor-based on-the-go nitrogen variable rate fertilizer systems have remained very modest everywhere (Lowenberg-DeBoer and Erickson, 2019). For example, Denmark is a country with a strong extension system, educated farmers and rigorous environmental laws, which, in theory, should encourage use of sensor-based nitrogen fertilizer systems; however, in 2021 only 2 percent of Danish farms used sensor-based fertilizer application (Denmark Statistics, 2021), amounting to only 4 percent of total crop area. Sensor-based, on-the-go variable rate fertilizer systems have been proposed for other soil nutrients (phosphate, potassium) and other soil amendments (e.g. lime), but not commercialized.

2.4 Autonomous crop machines

For decades, universities and research institutes have had prototype autonomous crop machines that they would demonstrate on parking lots and football pitches. A few were even evaluated in the field for specific crop operations (Lowenberg-DeBoer *et al.*, 2020). In 2017, Hands Free Hectare marked a turning point: it was the first public demonstration of how autonomous crop machines could be used throughout the growing season to produce and harvest commercial crops (Harper Adams University, 2018). In the last five years, major manufacturers of farm equipment have announced their autonomous machines (Table 1) and there are over forty 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 France has made the approximate number of robots public information. Lachia *et al.* (2019) estimated that there were 150 weeding robots used in 2018 in France, mainly for weeding organic vegetables and sugar beets. Similarly, in Northern America, various autonomous crop machines are starting to be commercialized, but quantitative estimates are rare. Erickson and Lowenberg-DeBoer (2021) estimate that 4 percent of agricultural input dealerships use robots for crop scouting services

and 2 percent use them for providing weeding services. However, those dealers expect substantial growth by 2024, with 18 percent expecting to offer robotic crop scouting and 13 percent expecting to offer robotic weeding. Crop scouting robots are used to gather very detailed information on plant conditions (e.g. weed infestation, insect populations, disease symptoms, 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.

2.5 Uncrewed aerial vehicles

Uncrewed aerial vehicles are the "robots in the sky." As ground-based autonomous machines, UAVs have been a popular topic for agricultural researchers and in farm media for the last few years. Most UAVs are used for information gathering, but they can also be used to automate input application. In most cases, UAV input application is like map-based VRT, while information gathering is a separate activity. An operator creates the application map, and 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. In the United Kingdom of Great Britain and Northern Ireland, UAV spraying herbicides is currently allowed only for applying herbicide to inaccessible location 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 percent of agricultural retailers in the United States of America provided UAV input application services that year. By 2024, 29 percent of those agricultural 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 Brazil and China. Kendall *et al.* (2022) provide survey data from the Hebei and Shandong regions in China's north 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).

2.6 Artificial intelligence

The potential for AI is much discussed in agricultural research, farm machinery manufacturing circles and the farm media (Coral, 2020; Cunningham, 2020; Jha *et al.*, 2019; Marr, 2019; Patrício and Rieder, 2018; Pauly, 2021; Peskett, 2020), but so far there are few examples of practical use. Combine harvester manufacturers claim to use AI in their operator assistance (Claas, 2022; Marr, 2019), but it is not clear how much machine learning is involved. Much of the combine operator assistance seems to be deterministic software that depends on conventional programming, such as table lookup. The use of AI in agriculture seems to mostly still be in the research and development pipeline.

While data is sparse, adoption of digital automation for agriculture in middle-income countries with substantial mechanized agriculture sectors seems to follow the same pattern as adoption in high-income countries (Griffin, Lowenberg-DeBoer and Lambert, 2005; Lowenberg-DeBoer and Erickson, 2019). For example, combine harvester yield monitor use started in Latin America and South Africa about the same time in the mid-1990s as it started in the United States of

America and western Europe. Early in the yield monitor adoption process, Argentina led the world in terms of percentage of combines equipped with yield monitors and GNSS. In the late 1990s it was estimated that 87 percent of yield monitors in Argentina were used with GNSS, compared to only a third in the United States of America (Griffin, Lowenberg-DeBoer and Lambert, 2005). Without GNSS to provide location data, yield maps cannot be made. This rapid adoption of yield monitors with GNSS in Argentina was linked to their structure of farming, with many large farms managed by professional farm managers. For those farm managers who rarely operate farm equipment the yield maps were new information, while in those parts of the world with more family farms, and therefore where farmers do more of the machine operation themselves, the yield maps helped quantify patterns of which they were already aware. Similarly, VRT fertilizer was introduced in Latin America and South Africa about the same time as it was started in Northern America and western Europe, and it has shown a similar mixed adoption pattern. For example, in a survey of large-scale commercial farmers in Brazil in 2013, 26 percent reported using VRT fertilizer, mostly with vary coarse sampling resolution (Molin, 2016). In the United States of America the most common sampling strategy is a roughly one-hectare grid, but in the 2013 survey in Brazil, only 16 percent of farmers used a grid of 1 hectare or less. Some Brazilian farmers reported using grid sizes over 9 hectares, which would not be considered precision agriculture in many other parts of the world. GNSS guidance is also being adopted in middle-income countries. An internet-based survey of Argentinian farmers in 2018 showed 60 percent were using GNSS guidance (Melchiori and Garcia, 2018). The 2013 survey in Brazil showed that already at that time 23 percent of farmers were using GNSS guidance and 14 percent were using lightbars. Anecdotal evidence suggests the GNSS guidance adoption is common on larger farms throughout Latin America and Africa. In general, GNSS guidance is being adopted almost everywhere where there is mechanized agriculture, and variable rate technology is still at the evaluation stage for many farmers, with widespread awareness of the technology but modest adoption levels. Variations from those general patterns of adoption are often related to crop choice, cost of capital, wage rates and other economic parameters.

Adoption of digital automation in agriculture for non-mechanized agriculture anywhere in the world is negligible. This non-adoption is largely because digital automation from mechanized agriculture does not transfer easily to non-mechanized farms and research to adapt digital automation for smallholder farm is almost non-existent. Almost no digital automation has been developed and commercialized with the non-mechanized smallholder farmer in mind.

3   Expected benefits of digital automation in agriculture

Consideration of the expected benefits of digital automation in agriculture 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. Availability of information on economic benefits varies widely among digital automation technology in agriculture. In this section, economic analysis of benefits will be presented for four technologies that have attracted the attention of economic researchers: robotic milking, GNSS guidance, VRT fertilizer 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 percent in some studies, but around 10 percent on average, (Hansen, 2015), and increased milk production, perhaps of 10–15 percent per cow (Drach *et al.*, 2017; Hansen, 2015; Steeneveld *et al.*, 2012). Steeneveld *et al.* (2012), for example, quantified the capital cost of automated milking at EUR 12.71 per 100 kg of milk instead of EUR 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.

While the labour required to operate robotic milking systems is minimal, human time and effort is needed to interpret the vast amounts of data collected by these 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 humans and animals (i.e. less contact between them) have also been explored (Bear and Holloway, 2019; Butler and Holloway, 2016; Driessen and Heutinck, 2015), although it is noted that data from automatic milking systems (AMS) can be used to identify health and welfare issues with stock. Introduction of AMS 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.

Overall, the conclusion that emerges from the research is that while the profitability of AMS varies from farm to farm, overall they reach breakeven, and farmers adopt the systems for the more flexible work schedule and quality of life benefits (Bergman and Rabinowicz, 2013; Castro *et al.*, 2015; Hansen, 2015; Vik *et al.*, 2019). Dairy farmers particularly appreciated the ability to spend more time with family and in community activities. It should be noted that, until very recently, most AMS were installed on small- to medium-sized family run dairy farms (i.e. between 100 and 300 cows). Often milking robots were installed as part of an intergenerational transfer on the farm given that the younger generation was interested in dairy farming, but not eager to take on milking cows two or three times per day. Recent anecdotal accounts indicate that large dairy farms (> 1 000 cows) install AMS due to concerns about hired labour availability. The decision to use robotic milking thus differs across dairy farms of different sizes.

3.2 Global navigation satellite systems guidance

The first published economics study on GNSS guidance was done in the late 1990s at Purdue University, with data supplied by the companies who first introduced GNSS (Lowenberg-DeBoer, 1999). The study focused on the benefits of GNSS lightbar systems because autosteer was not yet on the American market. It summarizes the qualitative benefits of GNSS lightbar guidance and quantifies the benefits of reduced skip and overlap compared to the foam and disk markers used up to that time. Skip occurs when the application passes are too far apart, such that some areas do not receive the input. To avoid skip, farmers with conventional technology often overlap input application passes, which leads to excessive, wasteful doses of input being applied. With manual driving overlap also occurs when the machinery turns on end rows. Thus, for custom operators, the reduction in skip and overlap from GNSS can cover the initial investment in the technology and show a modest benefit. The situation was similar for the many farmers who had already invested in GNSS for yield monitoring. Finally, the study predicted the growth of GNSS autosteer in agriculture based on technology that was already being used in construction and mining at that time.

Subsequent studies further confirmed the benefit and potential of related technologies. Watson and Lowenberg-DeBoer (2004) further considered autosteer technology, as well as the potential for farm expansion and controlled traffic. They concluded that autosteer would be profitable for many American farmers. Looking at the whole farm context, Griffin *et al.* (2005) evaluated the increase in timeliness from using GNSS guidance. Batte and Ehsani (2006) added sprayer boom section control to the analysis and concluded that its benefits were largest when used in irregular shaped fields and fields with obstructions like waterways, trees and rocks. Bergtold *et al.* (2009) estimated the benefits of autosteer in cotton production. Ortiz *et al.* (2013) estimated the benefit for autosteer for groundnut production. Griffin and Lowenberg-DeBoer (2017) examined the potential for reintroducing mechanical cultivation weed control in row crop systems using GNSS guidance. They found that, when herbicides were expensive or unavailable, mechanical weed control with GNSS guidance could help farmer avoid weed-related yield losses and maintain profitability.

The business case for GNSS guidance facilitated its adoption. The overall conclusion from the available research is that the largest benefits from GNSS guidance are a reduction in skip and overlap in input application. Reduction in operator fatigue, ability of family workers to work longer hours, flexibility in hiring drivers (i.e. driver skill is less of an issue), environmental benefits from reduction in overlapping applications and other more difficult to quantify advantages are treated as side effects in the adoption decision. The fact that benefits of GNSS guidance are realized quickly (e.g. input saving from reduction in overlap is almost immediate) and are visible to the farmer and the neighbours (e.g. reduced weed strips resulting from herbicide skips) also aid adoption.

3.3 On-the-go sensor-based VRT fertilizer

The economic benefits of variable rate technology of any type are linked to reducing input application and to optimizing crop yield. Environmental benefits are hypothesized when over-application of inputs is reduced in areas where those inputs are not needed to optimize yield. Fertilizer VRT was the first VRT to be commercialized and still represents the largest proportion of VRT application worldwide. Many evaluations of map-based VRT fertilizer also exist based on different soil nutrient variability data, different mapping making tools and varying application

equipment. Overall, those studies show mixed results of profitability (Lowenberg-DeBoer, 2018). Some show fertilizer reductions when compared to farmer practice and, more rarely, when compared to scientifically based extension recommendations. A few show overall yield increases. Companies sometimes advertise VRT as a cost-saving technology, although VRT fertilizer rarely reduces fertilizer expenses enough to cover the extra cost of testing the soil, making the recommendation map and variable rate spreading. To be profitable, VRT fertilizer often requires yield quality and quantity to increase. An example of yield quality improvement with VRT fertilizer is the higher sugar content of sugar beets when nitrogen fertilizer is site-specific according to the plant requirements and the soil nitrogen content. Sugar beet processors often pay a premium for higher sugar content beets.

The modest adoption of VRT fertilizer around the world can be linked to this mixed economic record. Farmers intuitively like the idea of putting fertilizer where it is most needed, but they are not convinced that with current technology it could be a profitable practice. Consequently, modest adoption estimates for VRT fertilizer suggest the technology is used only where it has proven consistently profitable (e.g. nitrogen on sugar beets, lime on soils with a very wide range of soil acidity), or by farmers that continuously hope that it will increase profitability.

Sensor-based VRT fertilizer has also been evaluated many times around the world (Colaço and Bramley, 2018; Lowenberg-DeBoer, 2018), mostly for VRT nitrogen fertilizer applications. Like map-based VRT, sensor-based technology depends on input cost reductions and optimizing yield for economic feasibility. In theory, sensor-based VRT fertilizer has economic advantages – e.g. sensor information often cheaper than soil sampling or other soil information source as fertilizer is adjusted by a computer algorithm, which does not require an agronomist for making the recommendation map. However, the literature shows mixed profitability results that are similar to that of map-based VRT fertilizer. For example, a partial budgeting analysis – which often focus only on short-term cash costs and yield benefits – shows that, out of 58 VRT nitrogen studies, about 25 percent showed economic losses (Colaço and Bramley, 2018). More complete economic analyses, which include the cost of equipment investment, training staff and other longer-term costs show an even higher rate of losses. Like the map-based VRT fertilizer, there is a modest level of adoption, reflecting farmers' interest in the technology and their efforts to find those uses for which the current technology is profitable.

One of the weak points of most commercial sensor-based VRT fertilizer systems is that they do not allow for differences in the productive capacity of the soil in adjusting fertilizer rates. To simplify the technology and reduce costs they often adjust fertilizer rates only based on sensor readings. For instance, crop colour may signal a lack of nitrogen to the sensor when the problem is in fact soil depth or another constraint. Diacono *et al.* (2013) reviewed 17 studies of precision agriculture for nitrogen management on wheat and recommend combining sensor data with soil maps, remote sensing images, yield maps and other data to tailor the nitrogen application to the site-specific constraints. Some crop nitrogen sensor companies are starting to introduce systems that combine sensor data with soil type and texture, previous yield and other field information in making fertilizer rate adjustments.

It is interesting to note that sensor-based VRT is one of the few precision agriculture technologies for which research has been done on medium- and small-scale farms in developing countries. For example, Ortiz-Monasterio and Raun (2007) tested use of a hand-held nitrogen sensor with wheat farmers in Yaqui Valley, Mexico. The use of the sensor when combined with a nitrogen rich strip for calibration saved farmers an average of USD 56/ha over

two crop seasons. A nitrogen rich strip is sometimes used with nitrogen sensors to provide information on the reflectance of the crop in that specific soil and climate when it has adequate nitrogen. Enough nitrogen fertilizer would be applied in that narrow strip to make it adequate for crop needs in all anticipated circumstances. Tobeh *et al.* (2012) review attempts to use hand-held nitrogen sensor technology in Africa. Hand-held crop sensors do not fit the definition of digital automated machinery, but their developing path is illustrative of the adaptive research and innovative business models that would be necessary to make digital technology available to small- and medium-scale farmers in low- and middle-income countries.

3.4   Autonomous crop machines

The assessment of the economic benefits of autonomous crop machines often starts with labour savings, and then extends to increased timeliness, greater accuracy of input application, and reduced soil compaction when using smaller swarm robots. Because autonomous crop machines are just starting to be commercialized, all the public economic analysis is extrapolated from research results. Lowenberg-DeBoer and Erickson (2019) did a review of published literature on the economics of autonomous crop machines. They found 18 studies, mostly partial budgeting analyses of automation of one field operation (e.g. seeding, weeding, 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. Lowenberg-DeBoer *et al.* (2021) used the Hand Free Hectare experience at Harper Adams University to estimate parameters for a linear programming analysis of autonomous crop equipment for arable farming in the West Midlands of the United Kingdom of Great Britain and Northern Ireland. They show that autonomous equipment has the potential to reduce wheat production costs by USD 20–30 per ton, cut equipment investment by more than half on some farms – by using smaller, lower cost equipment, such as swarm robots – and reduce economies of scale to the point that smaller-scale farms can achieve minimum costs of production. Shockley *et al.* (2019) developed a farm linear programme analysis based on autonomous crop machine prototypes at the University of Kentucky, United States of America. They showed the economic feasibility of autonomous crop machines for maize and soybean farms, and highlighted the potential for profitable use of autonomous crop machines on small- and medium-sized farms. Lowenberg-DeBoer (2019) used the Hand Free Hectare model to look at which farmers in the United Kingdom of Great Britain and Northern Ireland would be interested in autonomous grain carts, especially given how grain production harvest delays can lead to late seeding of subsequent winter crops and thus disrupt entire farming systems. He found that, with current wage ranges, farmers are usually better off with human-driven grain carts if they can hire workers reliably; when labour availability is lacking, using an autonomous grain cart might be a better option. Al-Amin *et al.* (2021) built on earlier analyses for the United Kingdom of Great Britain and Northern Ireland arable farms and showed that the swarm robot cost advantage is accentuated on farms with small and irregularly shaped fields.

Because some countries and states in the United States of America require on-site supervision of autonomous crop machines, Lowenberg-DeBoer *et al.* (2021) considered the economic impact of human supervision regulations. They found that, where 100 percent human supervision is required, the farmer is better off using conventional equipment. With current technology, if human supervision at the field is required, having a human drive the equipment

might be a better option. Maritan *et al.* (forthcoming) examined where 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 office at the farm) is optimal if the task to be automated is straightforward. They emphasize the need for greater AI capacity if the autonomous machine is to resolve more issues without human intervention. Shockley *et al.* (2021) extended the earlier Kentucky analysis to consider the economic impact of autonomous machine speed restrictions and found that, for maize and soybean farms, these can make the machines unprofitable.

Farm labour is becoming increasingly scarce, including in developing countries, especially as the rural young migrate to cities. The development of small, low-cost autonomous crop machines for small- and medium-scale farms can help fill labour gaps (Al-Amin and Lowenberg-DeBoer, 2021; Reddy *et al.*, 2016; Tarannum *et al.*, 2015; Valle and Kienzle, 2020); however, no publicly available economic analysis has yet been done on the use of autonomous crop machines in developing countries. Yet, the available literature on the economics of swarm crop robots highlights some of its benefits:

- The ability to reduce human manual labour in crop production with fairly limited investment.

- Relative to conventional machinery, it allows to reduce costs and economies of scale so that minimum production costs can be achieved for small-scale farms.

- Ability to farm small, irregularly shaped fields in a cost-effective manner, thus avoiding the need to reshape rural landscapes and disrupt communities to create the large rectangular fields on which conventional mechanization is most efficient.

4 Potential digital automation for agriculture in low- and middle-income countries

All of the digital automation adoption and economic analyses summarized so far in this report have been for mechanized agriculture in high- or middle-income countries. Research on precision agriculture for non-mechanized agriculture is growing (APNI, 2020; Nyaga *et al.*, 2021; Onyango *et al.*, 2021), but very little on digital automation. Furthermore, only few precision agriculture technologies for non-mechanized farms have been commercialized, with only anecdotal information being available on its adoption. Methodologies have been developed for manual site-specific fertilizer application – e.g. for VRT fertilizer on rice, see Witt and Dobermann (2002) – but no adoption statistics are available. The Agrocares hand-held soil scanner is available in several low-income countries in Africa and Asia (Agrocares, 2022) but very little information is available on use of the technology at the farm level (Van Beek, 2020). Non-mechanized farmers in Asia and Africa are using UAV services, but the number of farmers and area managed with UAVs is not well documented. The main use of GNSS on non-mechanized farms seems to be in mapping farm and field boundaries to establish land tenure (Lowenberg-DeBoer and Erickson, 2019).

Research indicates that site-specific crop management can improve yields and reduce input use on non-mechanized farms, but the cost of implementing this is often too high for low-income small farms. Hand-held nitrogen sensors are often priced between USD 300 and 600, which is too costly, especially for an individual small-scale farmer that would use the sensor only a few times per year, but even for extension agents or crop advisors that work with many farmers and use the device for several years. The Agrocares scanner provides information on a wider range of soil nutrients, but lists for over USD 3 000. Low-cost, donor-subsidized or venture capital-funded drone spraying is sometimes provided in developing countries, as the ones commercially available are often out of reach (Chikasha and Chipadza, 2021; Njagi, 2019). In South Africa even large-scale, mechanized farms may not be able to afford UAV spraying (Daniel, 2021). Re-designing these technologies so that they are less costly, as well as incentivizing mass production and innovative business models can make them more affordable for non-mechanized farmers.

4.1 Precision livestock farming for extensive systems

The status of precision livestock farming for extensive farms in developing countries is similar to that of precision agriculture for crops. The concept of precision livestock farming is well known (Adane, 2020; Laca, 2009; Neethirajan and Kemp, 2021; Walter *et al.*, 2017) and it is mostly used in intensive systems in high-income countries. Sensors are starting to be used to monitor health, the reproductive status and behaviour of animals, but these technologies are still too costly to low-income farmers and livestock herders. Low-cost livestock sensors could help growers diagnose health problems, provide appropriate treatment, avoid overuse of antibiotics and manage reproduction. EID and blockchain could help improve product quality by facilitating traceability of livestock marketed from extensive systems.

Among the precision livestock technologies that can be applied in low-income countries, virtual fencing systems come closest to being digital automation, as they reduce drudgery in addition to facilitating collection of information and intensive management. Virtual fencing uses audio alerts, electrical shocks or other prompts to keep animals within geolocated boundaries.

It potentially eliminates the need for physical fencing and the GNSS helps growers locate animals grazing in large open pastures. Sensors can be linked to the GNSS to monitor temperature, movement and other indicators of health and reproductive status. Virtual fencing could substantially reduce the labour requirement in extensive grazing systems and facilitate genetic improvement by improving control of reproduction, but the individual GNSS transponders required for each animal with current technology are too costly for these systems. As with crops, lower costs, mass production and innovative business models are needed to make these technologies available for extensive livestock production systems in low-income countries.

4.2   Uncrewed aerial vehicles for smallholder farms

While research is being conducted on UAV input application for small farms and commercialization has started, it is mostly map-based with very little autonomous decision-making capacity and consequently may not fit into the digital automation category. There has been research interest and some business start-ups focused on supplying UAV spraying services on smallholder farms in Africa (Ayamga, Tekinerdogan and Kassahun, 2021; Yawson and Frimpong-Wiafe, 2018). Unfortunately, robust data are not available on how widespread this practice is in developing countries.

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 remote and steep areas, and application to standing crops without damage to crops from equipment movement. For smallholder 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 creating systems to refill spray tanks, fertilizer bins or seed hoppers, increasing battery life, using pesticide labels for spot application, training users and reducing drift to non-target areas (Carvalho *et al.*, 2020). The profitability of UAV input application depends on the cost of the spraying service, the effectiveness of the application given drift, input savings and improved yields because of reduced damage from ground-based machines (e.g. backpack sprayer, tractor mounted or towed sprayer, fertilizer spreader or seeder, application with crewed aircraft). Because smallholder farmers are unlikely to own UAVs, the cost of the UAV application service is crucial.

For many researchers, research funders, entrepreneurs, politicians and venture capitalists, investing in autonomous crop machines for smallholder farmers is not worthwhile given their cost. However, as seen with mobile phones – which, in the 1970s, were very costly and inaccessible to most but now are often sold for less than USD 20 – technology improvement and high-volume manufacturing can make technologies much less expensive, and the prepaid business model is fitting to many developing counts. Mobile phones then paved the way for the introduction of smartphones, which are increasingly used for precision agriculture apps. In sum, the combination of technology change, mass production and innovative business models could do the same for autonomous crop machines.

4.3   A vision for low-cost 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 that could learn to seed,

weed and harvest for the price of a motorbike (between USD 500 and 1 000), which some smallholder farmers in low-income countries own, and therefore can serve as a useful price starting point. While a leg robot might be useful in fields as it can step over obstacles, they usually cost much more than 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 agroecology would be a high-cost, low-volume business. A more plausible business model would be developing a generic autonomous machine that is taught what it needs to do (perhaps by working alongside a human) and could be GNSS enabled to create maps (e.g. on soil colour, soil strength based on force required for hoeing, yield from plant-by-plant harvest). Appropriate tools for the autonomous machines would be adapted to the task and could be locally manufactured. There are several possible energy sources for the autonomous machines (e.g. fuel, solar, methane). To increase affordability, especially at first, rental or fee-for-service schemes 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 is what farmers now do when micro dosing (Aune, Coulibaly and Giller, 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 diseases and apply insecticides or fungicides as needed. Weeds could be controlled mechanically or with targeted herbicide applications.

This vision of digital automation for smallholder farmers represents an enormous engineering and entrepreneurial challenge, but it is conceivable with current technology and may be facilitated by innovations. The millions of smallholders in developing countries should be seen as an enticing market and a classic mass market business strategy as outlined by Prahalad (2004). A successful, relatable example is that of the spread of hermetic grain storage through Africa and Southern Asia (Nouhoheflin *et al.*, 2017) with the Purdue Improved Crop Storage (PICS) bag. At first, manufacturers were reluctant to invest because of the perceived lack of buying power of smallholders. However, after PICS sold millions of bags in more than 30 countries, many other competitors entered the market.

5 Broader implications of digital automated technology for the agricultural 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 United States of America in areas where the growing season was too short or summer rainfall too low for open pollinated maize. This was possible because hybridization gave breeders greater control over the maturity, drought tolerance and other agronomic characteristics. 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 automation technologies are developed and widely commercialized, the currently available research suggests that it could have major economic and social implications, including:

- **Farm structure**. Small swarm robots can provide almost constant returns to scale, whereby small farms can achieve 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 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 it does on profitability. By rapidly adopting swarm robots, areas in middle- and low-income countries currently 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 for agriculture as a high-tech industry, swarm robots also have the potential to retain the rural young and attract workers from other sectors.

- **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 to the abandonment of small and irregularly shaped fields or to their transition to less intensive uses, such as rural residences or hobby farming. This occurred in eastern United States of America in the early twentieth century. In other countries, such as in Europe, maintaining small farm structures usually involved high subsidy costs. The introduction of swarm robots may allow commercial agriculture to reclaim some of those small, irregularly shaped fields, which also have other economic advantages, such as high-quality soils, reliable rainfall and are close to markets. Small farm subsidy programmes may become less costly as swarm robotics help agriculture in small, irregularly shaped fields become more profitable. Farms dominated by manual labour or animal traction may skip motorized mechanization and move directly to digital automation, 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.

- **Introduction of swarm robots could radically alter the structure of the farm equipment market**. Major farm equipment manufacturers usually supply to, and interact with, a relatively small number of large farms. In contrast, swarm robotics would require mass marketing of

low-cost standardized products tailored to millions of small- and medium-sized farms. What the optimal business model will be 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 different from the current business model. This change in the customer base and in the business model may also change 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.

- **Digital automation with machine vision could make crop protection a service business.** Crop protection mostly entails selling large quantities of pesticides. Targeted spraying may reduce that quantity of pesticide used by as much as 90 percent, with significant environmental benefits. Mechanical or laser weed control may eliminate herbicides entirely. Depending on the business model adopted, this may strengthen the role of local entrepreneurs who train standardized autonomous machines to effectively identify the weeds and pests found on local crops. Those trained autonomous machines might then be provided under a fee-for-service model or sold to farmers.

It is important to note that none of these outcomes are automatic. 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, and social and cultural reactions. Furthermore, innovations using AI often depend on the availability of high-speed internet and other communication infrastructure. Governments and civil society can encourage positive outcomes from digital automation in agriculture through digital infrastructure, appropriate legal and regulatory approaches, and public sector research and education.

6   Impact of digital automated technologies on income distribution

The common perception of agricultural automation is that it will eliminate many rural livelihoods, create unemployment and exacerbate inequalities between large- and small-scale farmers. The loss of jobs to automation may occur most prominently for fruit and vegetable production where manual methods are still widely used, even in industrialized countries. However, because many industrialized countries depend on migrant labour for fruit and vegetable production, this is not primarily a domestic problem, 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 would be a mixed outcome because those jobs often lack good working conditions – namely, they often do not pay well, they force people to be away from their families for long periods of time, and do not have health or social benefits. Still, they provide a source of income, and therefore automation can be a bottleneck for low- and middle-income countries that depended on remittances from migrant farmers.

In the large-scale commercial arable farming sector, digital automation will likely entail a change in job types and responsibilities, but unlikely to lead to the loss of many jobs. In that sector, the major loss of jobs already occurred with motorized mechanization and chemical weed control. And given the potential increases in productivity linked to digital automation, farm workers who adapt and retrain could increase their incomes and have better living standards. For example, with digital automation, a former tractor driver may supervise a swarm of autonomous crop machines or learn to do repairs. With the reduction in economies of scale some former farm workers may also find entrepreneurial opportunities in small and medium enterprises.

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

Digital automation technologies can also create entrepreneurial opportunities. 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 an autonomous weeding machine 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 digital automation, organic production could undercut the costs of conventional methods and become the standard. Similarly, digital automation 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 at the same height on the stalk to facilitate harvest. However, in doing so, nutritional and culinary diversity was lost. Autonomous machines with AI could be developed to harvest traditional maize varieties with ears at different heights. Similarly, mechanized harvesting of tomatoes required varieties to ripen evenly. This, in addition to long distance supply chains, led to the development of new tomato varieties that lacked certain nutritional benefits and flavour. Autonomous harvest machines could allow for the commercial production of flavourful heirloom varieties. It could also create opportunities for the production of botanicals with

valuable aromatic or medicinal properties, which require intense management. Some of these opportunities could be generated also in low- and middle-income countries

In sum, if low-cost, highly effective digital automation in agriculture becomes as ubiquitous as mobile phones are now in low- and middle-income countries, then with the right 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 needed physical, economic and social infrastructure for digital automation stand to benefit; countries that ignore the challenge may not see the development of higher wage agricultural opportunities with digital automation. 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 uses of these 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). In some countries tractors have also become important for transportation within and off farms. Even in industrialized countries, farm products are often transported the first few kilometres in carts and wagons pulled by tractors. Some of the policy, regulatory and institutional issues that have been anticipated for digital automation technology include:

- **Appropriate guidance on human supervision of autonomous crop machines**. The European Union and the state of California, United States of America currently require, in most cases, on-site human supervision of autonomous crop machines. Research shows that, with current technology, the requirement of full on-site human supervision of autonomous machines substantially reduces their economic benefit (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.* (forthcoming) show that the economically optimal supervision level 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 countryside areas like those in most of Europe. In response to these concerns, the British Standards Institute (BSI) has organized an effort to create an autonomous agricultural machine code of practice for the United Kingdom of Great Britain and Northern Ireland. Factors that might influence appropriate supervision include:

  – 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 2.4 kilometres per hour. Under some ISO standards, autonomous machine categories are limited to less than 0.8 kilometres per hour. Shockley *et al.* (2021) 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 remote areas in Australia, than it would in relatively densely populated rural areas in the United Kingdom of Great Britain and Northern Ireland.

  – 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 swarm robots reduce soil compaction, increase soil health and facilitate higher yields, then a higher level of human supervision can be economically justified.

- **Training required for human supervisors of digital automation 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, TMA, and SPAA, 2021).

- **Digital automation often requires internet access**. 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 is particularly spotty in low- and middle-income countries. Policies to encourage 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.

- **Automation of all kinds requires energy**. This may be based on fossil fuels or on renewable sources (e.g. methane, solar, wind, hydrogen). Digital automation requires electricity. In countries where the electrical grid extends to rural areas, electricity is usually available only in towns, villages and farmsteads. Access to electricity in fields is rare even in industrialized countries. In many low- and middle-income countries, rural areas depend on off-grid electricity, if they have electricity access at all. Policies to encourage development and commercialization of off-grid electricity from renewable resources are important for widespread use of digital automation in agriculture.

- **Pesticide regulation for targeted application**. Many agricultural pesticide labels assume broadcast applications. Even with the best equipment and proper procedures, with broadcast application little of the pesticide reaches the intended pests (Duke, 2017). With targeted application, much more of the pesticide reaches the intended pests. In some cases, targeted applications at a higher than the current label rate would be effective, while at the same time reducing the overall amount of pesticide used. In the extreme, a few, more concentrated, amount of pesticide directly applied on the target pests would eliminate pesticide contamination of non-target species.

- **Data privacy and security**. Digital automation technology collects massive amounts of data on both crop and livestock farms. Some of that data may raise privacy issues for agricultural producers, agricultural households more generally 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 like e.g. livestock is 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 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. It 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 on what it learns. There is also the question of who owns the knowledge generated by machine learning (e.g. manufacturer, farmer, the contractor supplying robot services?).

- **Technical training and retraining**. Supervising digital automation, maintenance and repair of the machines and working with AI are not in the skillset of most of the agricultural workforce, especially on small-scale farms in low-income countries. What training is needed to supervise digital automation? Should programmes for digital automation maintenance and repair be started now, so that when the technology enters the market and is used 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 in 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. Most digital automation in agriculture will probably be privately owned, by companies or individuals, and the data it collects 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 digital automation technology?

- **Policies to encourage digital automation where it would have public good benefits**. Some aspects of digital automation in agriculture bring 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, managing extensive livestock production in natural areas without fencing). 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 certain digital automation technologies. For example, where upfront investment and retraining transition costs are substantial, public subsidies might encourage farmers to re-equip their farms with digital automation machines, instead of acquiring traditional motorized mechanization. The movement of agricultural research and educational institutions to the development and use of digital automation could be encouraged.

8 Summary and conclusions

This paper has shown that digital automation has been used successfully in agriculture for several decades (e.g. robotic milking) with newer technology in the pipeline to make digital automation ubiquitous (e.g. through mobile autonomous crop equipment). The discussion of the benefits of digital automation in agriculture usually starts with labour saving, but quickly moves to other benefits, including almost scale-neutral field operations, greater accuracy of input application, reduced soil compaction with small swarm robots, allowing field operations that are at times challenging to perform manually or with mechanical technology (e.g. due to wet soils or steep hillsides), allowing to automate the collection of crop and livestock data, and increased profitability for small and irregularly shaped fields. By rethinking and re-engineering the underlying science, many of the benefits of digital automation 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 small farms relying on manual labour and provide a basis for sensor-based fertilizer and pesticide application. If such low-cost, reliable and effective digital automation were developed and widely commercialized, it could radically change the farm sector. The dominance of large-scale farms using motorized mechanization would diminish, and medium and small farms everywhere would have a greater possibility of success. While digital automation has the potential of reducing some agricultural workers' livelihoods – a problem especially for countries supplying migrant agricultural workers to more developed regions – it also has the potential to create higher skilled, better paid job opportunities in rural areas (e.g. supervising, maintaining or repairing robots) and entrepreneurial opportunities. Realizing the potential benefits of digital automation requires 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 that encourage digital automation where it would bring public good benefits.

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Annex 1. Glossary

Agricultural automation: a general technology category that can be defined as the substitution of physical activities and/or human decision-making by machinery and equipment to perform agricultural operations, reducing or eliminating human direct intervention and improving their precision.

Artificial intelligence (AI): computer systems that analyse their environment and take actions with some degree of autonomy to achieve specific goals. Machine learning is often part of AI systems.[1]

Autonomous machine: a mechanical and electrical device that can perform certain functions without direct interaction with a human operator.

Autosteer: GNSS-enabled technology that provides automated steering and positioning in the landscape for self-propelled agricultural machines (e.g. tractors, combine harvesters, forage harvesters, sprayers). With the most advanced autosteer the computer does almost all the steering within the field including turning on the ends of rows. Autosteer technology typically requires a human operator in the seat of the machine to take over in case there is a malfunction or problem.

Backpack sprayer: an apparatus consisting of a knapsack tank together with pressurizing device, line, and nozzle for distributing liquids. The pressure can be created with a hand or motorized pump. They are used chiefly in fire control and in spraying pesticides.

Bolus: in ruminant livestock production a bolus is a large pill that can contain medication or sensors tracking the health and activity of the animal (e.g. temperature, movement). A sensor bolus can function in the rumen for several months.

Conservation tillage: any tillage and planting system that leaves a substantial portion of the soil surface with crop residue, after planting, to reduce soil erosion by water or wind. In many definitions at least 30 percent of the surface should be covered by crop residue. Conservation tillage types include no-till, strip till and ridge till.[2]

Conventional mechanization: non-autonomous machines which require human operators to accomplish farm work. Conventional machines may be powered by combustion engines, electricity, animal traction, human muscles or other power sources.

Digital automation in agriculture: a subset of agricultural automation that automates at least parts of both the physical work and the decision making.

Drone or **Uncrewed Aerial Vehicle (UAV):** a flying autonomous machine that can be remote controlled or fly autonomously using software-controlled flight plants.

Electronic Identification (EID): the use of a microchip or electronic transponder embedded in a tag, bolus or implant to identify an individual farm animal.

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[1] For more information see the European Commission's High Level Expert Group on Artificial Intelligence (2018).

[2] For more information see Conservation Technology Information Center (2002).

Fee-for-service: in the context of farm machines, this refers to a business arrangement in which the farmer pays for machine services on a per unit basis (e.g. per ha, animal, tonne harvested), rather than owning the machine.

Global navigation satellite systems (GNSS): any one of the national systems which use satellite signals to provide location information. Those national systems include the US Global Positioning System (GPS), the European Galileo system, the Russian GLONASS and Chinese Beidou system.

Global positioning system (GPS): the American GNSS, which was the first GNSS functional for civilian use; GPS is sometime used as a generic term for GNSS.

Leg robot: a mobile autonomous machine with articulated limbs instead of wheels for movement.

Lightbar: a GNSS-enabled technology which guides the steering of a human operator on parallel passes through fields. Typically it involves a row of light emitting diode (LED) indicator lights or a graphics display which tells the operator if they are to the left or right of the parallel track.

Linear programming: a mathematical optimization method that assumes that the objective function and the constraints are additive. When it is used for farm management, it can be thought of as automated budgeting.

Machine learning: computer algorithms that can identify patterns in data and improve machine performance based on those patterns without explicit human instructions. Machine learning is used by some AI systems to improve performance with experience.

Motorized mechanization: conventional mechanization powered by combustion engines. Typical fuels include gasoline and diesel.

Nitrogen rich strip: a nitrogen rich strip is an area of a field which has received enough nitrogen fertilizer to more than satisfy anticipated crop needs. Such a strip is sometimes used with nitrogen sensors to enable comparisons between reflectance on under fertilized areas and the reflectance of the crop in that specific soil and climate when it has adequate nitrogen. The nitrogen rich strip may also be labelled a "reference strip."

Operator assistance system: AI systems installed by original equipment manufacturers (OEMs) that help human operators of farm machines. Typically operator assistance systems integrate sensor data from several sources on the machine and automatically adjust machine settings to optimize the operator's priorities (e.g. fuel efficiency, work accomplished, product quality). They were first introduced on combine harvesters.

On-the-go: in the context of farm machines, "on-the-go" means that machine operation is adjusted while moving through a field based an algorithm using sensor data without direct human intervention.

Precision agriculture: a management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production (International Society of Precision Agriculture, 2021)**.**

Precision livestock farming (PLF): a data-based livestock management strategy that monitors and controls individual animal or group productivity, environment, health and welfare in a continuous, real-time and automated manner. It is focused on improving resource use efficiency, productivity, quality, profitability and sustainability of livestock production.

Prescription map: spatial information used to allocate crop inputs at different rates to areas within fields. Prescription maps are used to guide map based VRT.

Robot: a machine capable of autonomous operation without direct human intervention. The word tends to be used in the media and by the general public. Robots are often anthropomorphized. More technical discussions tend to use the terms like "autonomous machine" or "autonomous equipment".

Seeder row shutoff: a GNSS-enabled VRT approach that controls individual row seeder units based on a prescription map or sensor data. Often used to avoid seeding in non-crop areas or double seeding on end rows.

Skip and overlap: with conventional technology when applying fertilizer, pesticides and other crop inputs, farmers typically drive in parallel passes through the field. If the passes are too far apart there will be an area that does not receive the input application; that is a "skip". If they drive too close to the previous pass, the parallel application paths overlap, and some areas receive a double dose. Both skip and overlap are wasteful, but the skips are often the most visible, so farmers tend to overlap application. Depending on the driver and the equipment used, the overlap can often be 10 percent of the application width. GNSS guidance can reduce the overlap to less that 1 percent.

Sprayer boom section control: a GNSS-enabled VRT approach that can control sections of a farm sprayer boom based on a prescription map or sensor data. Section width may vary from several metres' width down to a single nozzle. Current technology allows nozzles to be turned on, off and pulsated a various rate.

Swarm robots: Multiple relatively small mobile autonomous machines that accomplish work done by one large machine in conventional mechanization.

Variable rate technology (VRT): equipment and software for varying application of fertilizer, pesticides, seed and other crop inputs within fields. Application rates can be varied either based on maps or sensor readings collected on the go within the field.

- **Map-based VRT:** a VRT based on a map that document spatial information on site-specific conditions within the field. That spatial information is usually organized in a separate work step by a human analyst.

- **Sensor-based VRT:** a VRT that is based on sensor reading collected on the go in the field. Typically, the sensor is at the front of the applicator, a computer that uses an algorithm to vary rates is on the machine and the application equipment is in the back of the machine.

Virtual fencing: this technology equips animals with GNSS transponders to determine their location and uses audio alerts, electrical shocks or other prompts to keep animals within geolocated boundaries. It potentially eliminates the need for physical fencing and the GNSS helps growers locate animals grazing in large open pastures.

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