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Drivers and effects of precision agriculture technology adoption in South Africa: Insights from selected sub-sectors

Alexis Habiyaremye
alexish@uj.ac.za
University of Johannesburg
Phumzile Ncube
University of Johannesburg
Kiru Sichoongwe
University of Johannesburg
Anele Slater
University of Johannesburg

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Abstract

The agricultural sector in South Africa is highly mechanized but has become increasingly vulnerable to the risks of droughts and other unpredictable extreme weather events, owing to the country's semi-arid climate. In the context of global warming, the adoption of precision agriculture technologies represents opportunities to optimize water resource utilization and mitigate such risks. Using a framework combining the 'technology-organization-environment' and the 'technology acceptance model', this study analyses the drivers and constraints of advanced digital technology adoption, as well as its implications on agricultural sustainability, productivity growth and employment dynamics. Our findings point to demand-side and organisational factors (such as global value-chain integration and economies of scale) as key drivers of precision agriculture technology adoption, while high capital costs and inadequacies in digital infrastructure were found to impede the adoption speed. Adoption benefits include productivity growth, operation cost reduction, optimized water resource management and skills upgrading. The uneven character of observed adoption patterns suggests the need for digital infrastructure expansion and customized support to increase smallholder access to digital technology services.

JEL classification codes: O13, O33, Q12, Q16, Q18

1 Introduction

Agriculture plays a crucial role in the South African economy, but it has become increasingly vulnerable to risks of drought as global climate change brings more frequent but unpredictable extreme weather events (Williams et al., 2020, Van Oldenborg et al., 2020, Otto et al., 2018. NASA Science, 2021).[1] Owing to the country's semi-arid climate, the capacity to effectively mitigate those risks remains constrained by the limited availability of water resources and the unevenly distributed irrigation infrastructure (Bonetti et al., 2022; Habiyaremye, 2020; Hudson, 2024; AgriMag 2023). The growing adoption of digital technologies for powering precision agriculture represents an increasingly important avenue to improve agricultural productivity while mitigating the risks associated with the effects of climate change exposure (Cisternas et al., 2020; Stankovic and Neftov, 2022; Guan and Grote, 2024; CeSTII, 2024). These technologies use sophisticated tools to optimize soil, water and fertilizer input management but their adoption has so far been lagging leading agriculture powerhouses (CeSTII, 2024). The aim of this study is to analyse the main factors driving or hampering the adoption of advanced digital technologies in a set of sub-sectors of the South African agriculture sector.

Precision agriculture technologies involve sophisticated digital tools and advanced skills, enabling farmers to apply a more detailed management of their agricultural inputs and processes, by leveraging accurate geospatial information, remote sensors, unmanned aerial vehicles (UAVs, commonly called drones), artificial intelligence (AI) and other digital technologies to provide crops and/or husbandry with a customized treatment (Barnes et al., 2019; Rejeb et al., 2022; Morchid et al., 2026). For example, the use of geospatial information systems enables farmers to customize their inputs and processes to the discerned variations in crop conditions, while AI helps them enhance their capacity to use complex data analysis for decision making, which results in higher efficiency, resource optimization, and better responsiveness to unforeseen variations (Sharma and Shivandu, 2024; Deng et al., 2018). Likewise, UAVs and remote sensors are deployed for the detection of crop condition, imaging, as wells as delivery of pesticides and fertilizers (Arab et al., 2022; Chavez-Martinez et al., 2026; Chen et al., 2026; etc). Sensors and AI are equally used to remotely control smart irrigation systems aimed to optimize water use (Morchid et al., 2026; Dhal et al., 2024; etc.).

A wider diffusion of these technologies among farmers can therefore be expected to increase overall efficiency and lead to more sustainable agricultural practices as well as to improvements in food security (Barnes et al., 2019; Morchid et al., 2026). These technologies are commonly characterized by a high degree of skills intensity and strong dependence on digital infrastructure, which imply considerable capital investments and maintenance costs (Barnes et al., 2019; Caffaro et el., 2020; Ogunyiola and Gardezi, 2022). The scale of production needed to recoup such investments within a reasonable period are often quite considerable. This has led to a rather slow adoption pattern, especially in developing countries (Dixit et al., 2023; Kudama et al., 2021).

As is the case in other African countries, South Africa is still battling to increase its industrialization in an effort to drive a new growth engine. Being one of the pathways to drive this industrialization strategy amidst increasing foreign demand for South African agricultural export produce, the government has been supporting the expansion of digital infrastructure to support precision agriculture (Cramer and Sender, 2023; CSIR, 2025). An example of this expansion is the adoption of a data-driven crop management digital platform developed by the Council for Scientific and Industrial Research (CSIR), in collaboration with the Agricultural Research Council (ARC) to enable users to access data on crop and soil health conditions based on satellite data. This nascent technology could bring significant technological shifts in the South African agricultural production system by making use of intensive digitalization. This in turn is expected to lead to the emergence of new agri-food systems that combine market demand priorities with sustainability in supply under constrained water resources. The complex nexus between the adoption dynamics of these technologies and the mechanisms through which they contribute to transforming our societies remains difficult to circumscribe, despite progress brought about by a multiplicity of studies in this domain (Rejeb et al., 2022; Ogunyiola and Gardezi, 2022; Gabriel and Gandolfer, 2023). This study aims to contribute to the growing literature on agricultural digital technologies by generating new evidence-based insights developed from close interactions with multiple stakeholders involved in the adoption and diffusion processes.

This paper uses a technology adoption framework combining Davis' (1989) technology acceptance model (TAM) with Tornatzky and Fleischer's (1990) technological, organization and environment (TOE) framework to analyse the adoption drivers and constraints of advanced digital technologies in the South African agricultural sector. From the TAM model, the focus is on the main elements of perceived usefulness and perceived ease of use (Pierpaoli et al., 2013). We also analyse the implications of technology diffusion on productivity increase, employee skills and employment dynamics (Habiyaremye et al., 2022). Based on in-depth interview data from a small but rich sample of key actors in the sector, the study scrutinizes the dynamics of technology adoption and diffusion as perceived and experienced by the adopters.

This study contributes to the ongoing literature on agricultural technology adoption by documenting the adoption experiences and patterns through a combination of diverse perspectives, ranging from adopting farming enterprises and technology service providers to industry association and government officials involved in adoption strategies. It also links technology diffusion to its implications for productivity and the skills requirements of staff at the adopting entity level. From an innovation diffusion theoretical perspective, it combines the insights from the technology-driven approach (Schmookler, 1966) with those from the market-pull perspective (Freeman, 1979).

Key results from our analysis indicate that while demand factors tend to be the main adoption drivers, adopter-specific characteristics play an equally important role, either as motivation factors or as constraints on adoption.

After this introduction, the remainder of the paper is organised as follows: the second section provides a brief literature overview to shed light on the dynamics of digital technology adoption that driving precision agriculture and related production systems. Section 3 explains our methodological approach. Section 4 presents the results of our analysis of data collected among respondents from various sub-sectors, with particular focus on the citrus sector. The paper concludes with a discussion of the results and policy recommendations in section 5.

2 Precision agriculture: digital technology types and adoption dynamics

Digital technologies characterizing precision agriculture have been pointed out as being a major driver of the new technological transformation to bring about more economic efficiency and environmental sustainability in the agricultural sector (Rejeb et al., 2022; Kolady et al., 2021; MacPherson et al., 2022). The deployment of a series of digital technologies and tools pertaining to the 4th industrial revolution (4IR), such as UAVs, robots, big data analytics, sensors, the Internet of Things (IoT), AI, and cloud computing makes precision agriculture a particularly potent mechanism for farm yield expansion, input cost minimization and farm management optimization (Guan and Grote, 202; Wolfert et al., 2017; Maschewski and Nosthoff, 2022; Zuo et al., 2021). The expected benefits of the intensification of precision agriculture are pointed out by various studies, with potential cost saving in agriculture input cost estimated to amount to billions of dollars

(Zuo et al., 2021; Impey, 2014; PWC, 2016). The use of UAVs in precision agriculture, for example, has helped to manage pests and diseases more effectively, to spot and provide image assessments of plant damage, to map weed development, analyse soil condition, efficiently apply fertilizers, spray pesticides, and optimize water use (Impey, 2014; Zuo et al., 2021). While the use of UAVs for the analysis of soil conditions has increased over time as they became more precise, farmers also use other state-of-the-art technologies such as remote soil sensors, giving them considerable real-time analysis benefits (Gebbers and Adamchuk, 2010).

Likewise, IoT helps optimize production processes by facilitating the integration of data on crop and soil conditions, weather characteristics and farm management systems (Rejeb et al., 2022; Morchid et al., 2026). IoT applications are used for multiple tasks in precision and smart farming, such as collecting weather and hygrometry data, as well as soil salinity levels and pest infestation. Such data are critical input that farmers use in to make real-time decisions aimed to optimize the effectiveness of their operations (Meola, 2016). In turn, IoT applications also generate extremely valuable data that are harvested to serve input for learning and adjustments in future decision-making (Zhang, 2025). IoT-enabled agricultural platforms can also be deployed to connect farmers with agricultural technology service providers, access extension service information, or contact operators when they wish to perform heavy or specialized agricultural tasks such as imagery or soil analysis (Maschewski and Nosthoff, 2022; Krishnan et al., 2020).

Continuous monitoring and analysis of the soil through sensors is used to achieve a heathier environment by optimizing the use of potentially harmful chemicals (Shafi et al., 2019). The information collected from sensors can be stored and used to determine the efficiency of farming methods, as well as for market analysis and logistics (Western Cape Department of Agriculture, 2022). The use of advanced agricultural robots equipped with high-resolution computer vision, smart sensors and artificial intelligence contributes to intensifying the automation of various farming operations such as planting, animal feeding, fertilizer or pesticide application, weeding, autonomous milking systems and even complex harvesting tasks (Gabriel and Gandorfer, 2023; Oliveira and Martins, 2011; Shamshiri et al., 2018; Manisankar et al., 2022).

The literature on the adoption of advanced digital technologies in agriculture has used various theoretical frameworks and diverse empirical techniques to explain the patterns, drivers, constraints and the dynamics of adoption under different settings. Pierpaoli et al. (2013), for example, proposed a conceptual construct based on two main facets of the ex-ante TAM framework to serve as an encompassing framework to interpret the adoption of precision agriculture technologies by agri-business enterprises. This construct combines the perceived usefulness of the technology with considerations regarding the perceived ease of use as the basis for explaining actual adoption behaviour. Perceived usefulness is defined by Davis (1989:320) as “the degree to which a person believes that using a particular system would enhance his or her job performance”, while perceived ease of use is defined as “the degree to which a person believes that using a particular system would be free of effort”.

These constructs portray ex-ante attitudes towards technology adoption as being driven by a wide set of factors that are grouped into three categories: socio-demographic factors, which characterize the would-be adopters, the competitive and contingent factors affecting the adopting agricultural enterprise (such as the farm size, extension services, the market and export structure), and the factors affecting its financial resources, such as the cost of the technology and the perceived benefits (Habiyaremye et al., 2024). This model has significant overlaps with Rogers’ (1995) diffusion of innovation (DOI) theoretical factors. The theoretical construct provides a schematic summary of the effects of these different factors on the adoption attitude, as shown in Figure 1.

Some empirical studies examining the structure of influences on the adoption of precision agriculture technology combining the ex-ante expected drivers and a post-adoption analysis of determinants have revealed a consistent picture: some of the most important factors are the size of the adopting farm, the potential for cost reduction or higher profits, the expected total income, among others (Gabriel and Gandorfer, 2023; Pierpaoli et al., 2013; Tey and Brindal, 2012). The typical profile of the adopter is an educated farmer with a large farm (bigger than 500 ha) and with a good familiarity with computers, looking for technologies enabling them to face competitive pressure and achieve higher profitability Tey and Brindal, 2012). Moreover,

Saengavut and Jirasatthumb (2021) argue that small-scale farmers' decision-making processes are also driven by perceived benefits and the younger generation's openness to adopt emerging technologies.

FIGURE 1 HERE

Tornatzky and Fleischer's (1990) technology adoption theory, the TOE framework, categorizes drivers and constraints to technology adoption into factors related to the characteristics of the technology itself, those related to the adopting organizations and those related to the adoption environment. Technological factors may include aspects such as the perceived benefits of the technology, its complexity and its availability, as well as the presence of corresponding technological infrastructure to enable its deployment (Narula, 2004; Weil and Broadbent, 1998). Organizational factors are related to considerations such as scope, size, organizational structure and human resources, while environmental factors refer to exogenous influences and other industry stakeholders such as competitors, government regulators, suppliers and customers (Nautwima et al., 2025; Oliveira and Martins, 2011). Organizational characteristics that facilitate adoption include absorptive capacity of potential adopters (Cohen and Levinthal, 1990; Narula, 2004; Criscuolo and Narula, 2008), their managerial attributes (Aboelmaged, 2014; Awa et al. 2017; Rogers, 1995), their size and potential economies of scale (Na et al., 2023; Schumpeter, 1942), as well as their attitudes towards risk (Awa et al., 2017; Van den Berg and Van der Lingen, 2019). Policy uncertainty, lack of political support, availability of external financing, as well as weak compatibility with established norms and values may constitute additional exogenous impediments to technology adoption (Foxon and Pearson 2008; Khurana et al., 2023; Narula, 2004; Rogers 1995).

On the market demand side, extant literature suggest that international quality standards and participation in global value chains are commonly accompanied by the adoption of more sophisticated technologies to meet concomitant requirements (Makriet et al., 2017; Atkin et al., 2017; Zeng et al., 2025; D'Angelo et al., 2020; Golovko et al., 2023). Being an exporter facilitates both access to advanced technologies and increases the probability of reaching the production scales and efficiency that makes it more likely to recoup the necessary capital expenditures and maintenance costs (Seker, 2012; Melitz, 2003; Hirsch and Adar, 1974)

The most common barriers to adoption include costs (adoption costs, resource adaptation costs and regular maintenance expenses), technology relevance, its user friendliness, high skill requirements to operate the system, mistrust of algorithm-driven systems, and adoption risk (McFadden et al., 2023). The digitalization of agricultural systems can also be hampered by the unavailability of the internet and coverage by mobile digital network infrastructure, the cost of internet connection devices and data (Aguera et al., 2020). The adoption of many agriculture precision technologies such as IoT applications may also be hampered by their reliance on sophisticated cloud computing infrastructure and digital platforms dominated by powerful foreign corporations, with the potential to use cloud monopoly or oligopolistic control structures that leave farmers at their mercy (Wolfert et al., 2017).

Owing to multiple factors ranging from digital infrastructure to the scarcity of relevant technical skills, the adoption of precision agriculture technologies has been slow and uneven, despite their expected benefits, especially in developing countries (Kudama et al., 2023). Understanding the determinants of their diffusion is therefore critical to generating reliable insights into how such technologies are transforming the agricultural sector and what policies are most appropriate to steer that evolution in the desired direction (Ogunyiola and Gardezi, 2022; Gabriel and Gandorfer, 2023). The next section presents the methodology used in the study.

3 Empirical Methodology

This study used primary data in a qualitative format. The data were collected through 12 online interviews held with a sample of key players in the South African agricultural system between August and October 2023. The goal of the data collection was to understand the processes involved in innovation and the adoption of the most recent advanced technologies in South African agriculture. We employed a cross-sectional survey design and a non-probabilistic snowball sampling approach. Potential respondents were identified through internet scoping research. During the scoping exercise aimed to identify study participants, we targeted both the users of advanced agricultural technologies and the suppliers of these technologies. This choice was made with the view to gain a deeper understanding of the demand-side factors affecting the decisions made by farmers and agribusiness groups to acquire and use advanced technology in their operations. From the suppliers, we sought to ascertain what drove their supply dynamics in the South African agricultural landscape, and what they understood to be the reasons for their customers' adoption of advanced technologies for their farming operations.

Naderifar et al. (2017) note that the snowball approach, which is frequently employed in qualitative research, is useful when targeting populations that are not easily accessible. It is difficult to find farmers or agribusinesses through internet searches, as many of them do not have websites or online profiles. From the respondents who agreed to participate in the study, we requested referrals to other potential study participants. This technique depends on the notion that study participants of the target population are embedded in social networks of other players with similar characteristics who can be recommended to researchers (TenHouten, 2017).

The interviews were conducted based on semi-structured interview guides and involved 12 participants from different segments of the South African agricultural sector. Respondents were identified among fruit, crop and livestock farmers, industry associations, government department and a technology service supplier. Out of these respondents, four were from different sections of the citrus sub-sector. Unlike the other respondents, whose inputs were mainly related to the use of technology in the pre-harvest stages (for example farming of fruits, growing of livestock and so on), the respondents from the citrus sub-sector represented both pre- and post-harvest stages, namely nursery, growing of the fruit and the packing stage. This study includes a separate analysis of advanced digital technology adoption in the citrus sub-sector.

Ethics approval for the study was obtained for the research project as mandated by the University of Johannesburg under Ethical Clearance Code: 21SECO036. The respondents of the study were provided with an informed consent form as part of the interview request. All the respondents provided their consent verbally during the interviews. The anonymity of the respondents is upheld, and the respondents are not identified in any way in the article. The breakdown of the respondents by type is found in Table 1.

Table 1: Interview respondents by type

Respondent type	Number
Farmers	4
Packhouse	1
Industry association	4
Government department	1
Technology supplier	1
Other stakeholder	1

TABLE 1 HERE

The data analysis sought to identify the technology that was adopted by the respondents and to analyse the drivers of technology using the TAM and TOE frameworks of technology adoption. A key limitation of the study is the relatively low response rate. This is largely due to the difficulty of finding farmers or farmer groups willing to participate. However, we were

able to mitigate this by speaking to industry associations covering a wide array of sectors (fruit, commodity crops and other agribusinesses) who were able to provide a broad outlook of their members.

4 Drivers, constraints and effects of advanced technology use

This section provides a description and analysis of the technology used, drivers of and constraints to technology adoption, and the effects of adoption on factors such as skills and employment in various sub-sectors. The analysis of the use of advanced technology in agriculture can be split into pre-harvest and post-harvest components. The pre-harvest analysis includes technology used in nurseries, farming of crops and rearing of animals. The post-harvest component of the analysis comprises mainly an analysis of the technology used in packhouses and abattoirs. Unless otherwise stated, the information in Section 4 is based on the interview data from the respondents.

4.1 Description of the advanced technologies used in South African agriculture

4.1.1 Pre-harvest use of advanced technology in SA agriculture

One type of advanced digital technology can be observed in the systems used to set up and monitor weather-controlled environments. These environments enable farmers to set the ideal weather conditions, such as controlling temperature or humidity, either for livestock production or for horticulture farming. In poultry farming, poultry houses are equipped with computerized management systems. If any problem arises, such as chickens coming under distress, the system parameters are set to trigger an alert to be sent to the farm manager via mobile technology, so as to prompt them to act immediately.

Similarly, in horticulture nursery tunnels, when temperatures rise above a pre-determined level they spray water, and when they drop too low the temperature is adjusted. This specific technology led to the respondents producing better quality plants, preventing loss due to extreme temperatures, and allowing the year-round production of seedlings. Another technology that has revolutionized farming practices is the use of UAVs in various farming tasks. For instance, UAVs have been used to carry out field assessments of soil and plant health, administering pesticides, and for surveillance on the farm to monitor security.

Farming applications such as ‘Fieldmargin’ and ‘FieldView’, are used to simplify multiple farming activities. ‘Fieldmargin’ is farm management software that helps farmers to map their fields and do real-time monitoring of weather data and satellite imagery. ‘FieldView’ is a precision agriculture platform that provides farmers with advanced data visualization and predictive analytics to maximize production and crop yields. These applications assist in overlaying aspects such as soil mapping and plant data to make the work more efficient.

Satellite imagery is deployed for soil classification based on physical properties and chemical analysis. This process allows soil mapping and access to specific soil maps, and includes water analysis. Satellite imagery also enables leaf sampling and foliar analysis. These samples are tested in laboratories for carbohydrates in plants and to monitor their status during certain phenological stages. This type of data is used to identify areas with high potential or areas requiring fertilizer application and hereby optimize soil utilization potential. This helps to use the soil potential efficiently.

Other types of software are those such as the integrated farm management software known as ‘FarmNode’. ‘FarmNode’ consists of various modules, including irrigation monitoring, pest management and fertilizer management used in conjunction with sensors. The irrigation module consists of soil probes known as capacitance probes, and in some cases tensiometers, that are used to record soil moisture levels. The probes are continuously logging soil moisture data, and these data are saved in the cloud. The moisture data in the monitoring stations is entered into tablets by scouts, and this information is used to make decisions on how much irrigation is required. A schematic representation of the automated irrigation module is provided in Fig. 2.

FIGURE 2 HERE

The pest management module uses information gathered by the scouts to determine the type of pests, the size of the area affected and which chemicals to apply. The fertilizer module keeps track of fertilizer applications and records corresponding data. Fertilizer usage data tracks the amount of fertilizer used in each block of trees.

In addition, respondents noted that GPS guidance systems are fitted onto tractors. To further optimize the digitalization of the tractors, tractors can be set up with auto-steering technology enabling them to perform the assigned farming tasks autonomously, based on data encoded into the GPS guidance system. The digitised tractors are used to track the progress of farming operations such as spraying, fertiliser application, and sowing has been done. This information can be used with the pest management information gathered by scouts to ascertain whether interventions have been successful. Moreover, the tractors can use IoT to connect with one another, which allows for remote monitoring of irrigation and planting.

Livestock farmers also use precision technology to monitor their herds. One livestock farmer stated that they use an air tag system called RFID which is attached onto each animal's ear. The RFID tags are useful for various elements of monitoring. For example, when the animals are weighed, they automatically connect, identify the animal, its location, its weight when it arrived, its feed, whether it is ready to be slaughtered and so on. From an adaptive mechanization perspective, the respondents identified Bluetooth callipers which measure the size of the fruit and send the information to the relevant software. There have been further advances in this technology in the form of sensors that are placed on the fruit and are constantly measuring and taking photos of the plant. The Bluetooth callipers are a cheaper option for monitoring plant growth, and easier to use while still less time-consuming than physical measurement and capturing.

Hydraulic pruning shears are another example of adaptive mechanization and have replaced pruning by hand. This technology has increased the productivity of the workers, who are able to prune up to 200 trees per day compared to 100 trees when pruned by hand. Although these technologies are not as advanced as some of the precision agriculture tools, they have still resulted in positive benefits for the respondents in terms of higher productivity of the workers, and less time-consuming but more accurate measurement.

Finally, gene technologies and artificial intelligence are also among advanced technologies adopted by players in the South African agricultural sector to improve crop and livestock breeds. For example, beehives are commonly used with AI systems and cameras by grain farmers for pollination and monitoring to count bees in orchards with the aim to optimize the pollination of crops. Similarly, some livestock farmers use DNA testing to track the presence of the polled gene (naturally dehorned cattle), to track the marbling scores of beef, and maternal factors of cows such as they type of milk they will produce which enables them to focus on breeding stronger genetics in the herd.

The deployment of these technologies has led to doubling the yields of crops and livestock.

4.1.2 Post-harvest use of advanced technology in agriculture

The main post-harvest activity is the packaging of both meat products and crops. For crops, particularly horticultural crops, packaging primarily takes places in packhouses. According to one of the respondents, the most advanced technology is mainly deployed in the packhouses, even as varying degrees of automation can be observed within the industry. In a typical citrus packhouse digital control begins with the automation of the wet line, where the fruit is cleaned, sanitized and protected with post-harvest chemicals before being dried and protected by a wax system. Then the automated grading machine allocates each fruit to a class depending on its size, appearance (including colour and the presence of markings such as blemishes) and shape (whether it is more oblong or round). This is done with a camera system that takes more than 20 photographs of each fruit and rapidly scans them to accurately determine the correct market destination and to ensure that only fruit that meets the requirements and criteria of the corresponding client are packed for said client. The grading and sorting system is calibrated with the parameters required by each specific destination (e.g., Europe, USA or Australia), the specific client, the labels, and the packaging dimensions.[2]

For meat, such as poultry farms, there are software management systems that are used to maintain the chillers at a certain temperature, to ensure that the meat is processed at the correct temperature and to identify damaged birds.

The egg packing stations also use technology through an automatic grading system where the eggs are dispatched onto a conveyor belt. Similar to the citrus system, the grading system scans the eggs to separate them according to size, identifies and rejects damaged eggs (which can be processed further as liquid eggs).

Table 2 provides a summary of the main pre- and post-harvest technologies identified by respondents as having been adopted for use in farming.

Table 2
A selection of 4IR technologies used in South African agriculture

Farming domain	Technology	Application domain
Livestock production	Automated detection using artificial intelligence	Monitor poultry health
Crop production	GPS guidance, UAVs	Soil and plant health monitoring, administering pesticides
	Satellite imagery	Soil classification & soil chemical property analysis. Soil mapping and fertilizer application
	Farm management software: 'FieldView' & 'fieldmargin'	Precision agriculture digital systems providing advanced visualization & predictive analytics to help optimize crop yield
	GPS-guided tractors & IoT-connected farming tools	Autonomous planting and fertilizer application in precision agriculture
Plant breeding	Gene technology &AI	Biotechnology, AI for monitoring plants and bees for pollination
	Temperature monitoring in nurseries	Optimization of plant breeding quality
Animal breeding	Gene technology	Determing marbling of meat, maternal characteristics
Plant growth monitoring	Sensors and UAVs	Imagery and data collection enabling timely interventions for pruning, pesticide spray, etc
Packhouse	Auto-tipper, grading system, outlet system	Grading system allocates fruit or eggs to relevant customer or tray Outlet system packs fruit into correct packages

Table 2 HERE

4.2 Drivers, constraints and effects of technology adoption is South African agriculture

4.2.1 Drivers

Technology adoption by farmers was assessed to be driven by several factors, determined by both the TAM and the TOE frameworks. Based on the TOE framework, the main factors to be considered are technological, organisational and environmental factors. At the same time, these factors could be linked to those in the TAM framework, namely socio-demographic, adopter's attitudes towards technology, financial resources and competitive and contingent factors.

Technological factors can be linked to financial resources and affordability of technology, organisational factors can be linked to socio-demographics and adopter's attitudes towards the technology, while the environment can be linked to the competitive and contingent factors.

Among the organisational and socio-demographic factors, large scale farmers were found to be more likely to adopt advanced technologies, since they tend to have more access to the resources, the scale of production and the market linkages that facilitate their capacity to recoup the investments. By contrast, smallholder farmers, tend to be less likely to adopt the most advanced technologies as their scale of production is often too small to warrant the rates of return that can cover the financing and maintenance costs. Age also plays an important role as younger farmers tend to be more equipped with the set of skills that facilitate new technology adoption.

In terms of factors derived from adopter's attitudes towards innovation and technological change, respondents identified demonstration effects of technology adoption as having a significant influence on such attitudes: farmers tend to adopt technologies when they observe them in action at other farms. This imitation effect was observed to be particularly frequent among small-scale farmers. The sharing of information between farmers is therefore essential in speeding up technology diffusion. Perceived improvement in farm management is an equally important driver for technology adoption as farmers attach value to efficiency and optimization of resource allocation.

For technological factors, specifically those related to the characteristics of the technology itself, the principal driver for digital technology adoption such as irrigation and pest management is its advantage in reducing the time spent on collecting and capturing information obtained from plant and soil monitoring. This corresponds to the technological dimension encompassing the perceived benefits of the technology and the technical competence of the staff (Rogers, 1995; Nautwima et al., 2025). Automated capture enables users to make more timely decisions and therefore helps optimize resource utilization and yield maximization.

For horticultural farmers such as citrus producers, one of the main technological factors is the need to operate at significant scale to push the volumes required within a specific period, given that the process deals with seasonal and perishable products. This necessitates the completion of packing and packaging within a short time span. One of the respondents confirmed that their biggest constraint was moving large enough volumes through the packhouse, grading the fruit and packing it within approximately a week after picking. The automated grading system has capacity to process approximately 5000 tons of fruit per week, which is a much higher volume than what the throughput would be, were it to be done manually. Another respondent commented that it would be "impossible" to grade the fruit by eye for blemishes and phytosanitary issues at the required volumes and levels of complexity.

For technological factors linked to financial resources, the cost of adoption and access to bank credit were the most recurrent drivers identified by respondents. Before adopting a technology, farmers consider competitive advantage and cost savings, with the aim to enhance productivity and reduce risks. Low-cost equipment is most attractive for technological upgrading, especially among smallholder farmers. Conversely, high adoption costs tend to temper the enthusiasm for adoption, even when the corresponding technologies are seen as reliable and transformative. Environmental factors were also identified as key drivers. Among environmental factors, specifically competitive and contingent factors, participation in value chains was found to have a significant influence on how farmers use technology via vertical coordination and spillover effects. Technology use within a value chain opens access to holdup opportunities inside the value chain and even in technology markets.

In horticulture, particularly in the citrus sub-sector, a key environmental driver of technology adoption is the competitive pressure for ever increasing quality to meet domestic and export market demand. Market requirements in terms of fruit size, visual appearance, taste, and other specifications such as ease of peeling, have become a very important consideration to compete effectively in global markets. As many of such attributes are determined by irrigation and fertilizer application, an accurate dosage and timing of water and fertilizers is crucial. The third major reason for adopting digital technologies is the necessity to comply with bureaucratic regulations aimed to adhere to customer standards and international certification of

best practices. Foreign customers generally require their suppliers to have certifications such as the Global Good Agricultural Practice (Global GAP), 'Farming for the Future' and Rainforest Alliance. These certifications require regular audits that collect information on water usage, fertilizer applications, and chemical or pesticide usage to determine whether the suppliers are applying responsible and sustainable farming practices.

Environmental factors can also include the necessity to handle high volumes while serving multiple markets with diverse quality requirements. Citrus producers who supply to multiple export destinations need to use digital technology to ensure different customer requirements are accurately matched with the quality grades within a minimum sorting time in the packhouse. While grading automation is not a customer requirement, it allows the packhouses to comply with their throughput targets while handling the harvest of multiple citrus producers. The post-harvest processing has the most advanced technologies, while the harvesting stage has virtually no automation, since each fruit must be picked with extreme care to avoid any mechanical damage that would compromise quality.

4.2.2 Constraints on Technology Adoption

Counter to the drivers, constraints hamper the adoption and diffusion dynamics by limiting the benefits that farmers can expect from the adoption. Such factors include limitations in access to financial resources, limited scale of operation, high cost of technological systems, lack of commensurate skills and high costs of digital infrastructure services. For example, it is estimated that only about 25% of small-scale black citrus farmers are actively adopting precision agriculture technologies, due to a lack of resources. However, a programme set in collaboration with the government to provide agricultural extension services and facilitate their access to finance has allowed them to begin adopting these technologies.

Profitability and the long-term financial sustainability of technology were also cited by respondents as important constraints. When farmers do not have access to critical information about how profitable technologies are, they are less likely to adopt. Their adoption behaviour is often based on well-being maximization, which they perceive to be primarily determined by productivity and income.

As previously mentioned, software such as "FarmNode" is used in SA agriculture. The principal hindrance to its adoption is the deficiency of the domestic digital network infrastructure on which it is dependent, but whose coverage often fails to reach remote areas and deep valleys where the citrus plantations are located. Owing to frequents blackouts in electricity supply, the 4G networks suffers from disruptions and no alternative digital data-transmission infrastructure is available.

4.2.3 Effects of digital technology adoption on productivity, skills and employment dynamics

The adoption of advanced technologies in farming has decreased the amount of manual labour that many farmers need to operate. Utilising technology allows farmers to fully optimise their operations, leading to increased efficiency and output. However, the effects of advanced technology adoption on employee skills, productivity and employment dynamics, exhibits differences between commodity sectors such as poultry or grain farming compared to high value agricultural sectors such as horticulture farming.

In the poultry sub-sector, certain farm tasks and even jobs have become obsolete because of the increased use of technology and automation in the industry. As a result, jobs are threatened by the forces of automation and technology. In the horticulture sub-sector, the observed outcomes indicate a close connection between increase in automation and skills upgrading, higher efficiency in quality control, substantial cost and wastage reduction, and more sustainable production practices without any loss of employment. The use of sensors with digital agricultural technologies such as 'FarmNode' in the management of a nursery (i.e. in a controlled environment) enables growers to produce high-quality trees all year round and reduce losses due to freezing. The result is higher productivity overall, which translate into higher quality of the final product as well.

In recent decades, blueberry production has seen a significant transformation due to the introduction of new technology and scientific advances. However, jobs in the blueberry sub-sector have not been displaced because of technology use since there are not many automated fruit farming operations. The skill level of farm labourers remains significant in determining the effective adoption and usage of novel technologies. A lack of competent skills could cause adoption to lag, which would have a big impact on how the technology is used.

For citrus farmers, the observed cost reduction generated by the automation of the system is attributed by respondents to the significant savings in water and fertilizer use, as well at the increase in the accuracy of quality control, which enables the packhouse to treat larger volumes during the height of the picking season. The increase in precision of the fruit grading system also enables the packhouse to better plan the packing and avoid fruit over-maturation. Handling larger volume with higher efficiency leads to new skills specialization (requiring most employees to reskill and become computer literate) without employment shedding, as saved unit labour inputs are absorbed by production expansion. This result is very significant since technology adoption usually carries the risk of employment displacement, which remains of particular concern to the South African economy constantly battling the highest unemployment rate in the world (Habiyaremye et al., 2023; Magome, 2023).

Employment shedding is avoided by removing manual tasks from the production system and deploying labour in specialized skills in complementarity with the automated systems:

Automation takes the tedious manual tasks out of the system so that people can focus more on managing and doing quality checks. We don't have less people, but we're packing more fruit … We still have 60 to 70 people working in the packhouse, but we are packing 200 tons where we used to pack 100 tons per day (Interview, 12 October 2023).

The adoption of precision agriculture technologies has implications for the sustainability of the agricultural production processes as well: by facilitating the scouting and tracking systems that enable the targeted and optimized use of irrigation, pesticides and fertilizers, which leads to considerable savings in water usage (up to 24% of irrigation water in comparison to traditional irrigation systems) and a considerable reduction in pesticide use. Automated systems also enable the storage of information on the production process, which in turn facilitates traceability check by connection retailers, who can more easily assess the sustainability of the production methods and respond to queries by consumers.[3]

Table 3 summarizes the main drivers, constraints and effects of advanced technology adoption in South African agriculture.

Table 3
Drivers, constraints and effects of advanced technologies in South African agriculture

Factor dimension	Main drivers	Constraints	Effect
Technological factors (financial resources)	Affordability of technology costs. Profitability and long-term financial sustainability.	High adoption and implementation costs Availability of complementary technological infrastructure Technology platforms controlled by large multinationals	Operational efficiency, higher productivity and cost reduction Optimization of production planning and reduction of wastage Increase in scale and expansion of the scope of output Shift of farming operations towards more skills-intensive methods No observed employment shedding: efficiency gains are translated into scale extension whereby technology and labour remain complementary
Organizational factors (socio-demographic factors; attitude towards technology)	Technical competence of staff Demonstration effects: farmers adopt technologies used by other farmers. Profitability and long-term financial sustainability Positive attitude towards change Farm size: large commercial farms mainly producing for export Volume and throughput targets within specified period Age of farmers (younger farmers tend to be more likely to have the skills set required for a quicker adoption).	High costs and access to financing Small size of some farming enterprizes limiting economies of scale. Limited skills pool to drive technology adoption Scale: Need to package perishable goods within short space of time Lack of access to information; lack of technical skills to effectively implement the adoption.	
Environmental factors (competitive and contingent factors)	Linkages to value chains and export market participation Competition pressure in export market Sophisticated and complex export market quality requirements International certification and standards Volumes required by export market	Cost of digital infrastructure services, e.g. network data Limited access to IT network coverage Environment regulations Lack of access to new skills training to prepare older farmers to new technologies	

Source: Adapted from Pierpaoli et al. (2013)

Table 3 HERE

5 Discussion and concluding remarks

This study has explored the dynamics of advanced technology adoption in the agricultural sector in South Africa. The analysis focused on drivers, constraints, as well as the effects of the adoption of these technologies on skills and employment. The observed agricultural technology adoption patterns in the considered sub-sectors in South Africa reflect the dynamics of their specific technological, organizational and environmental factors within each sub-sector. They are in close alignment with the main features of perceived usefulness and ease of use highlighted by Pierpaoli et al. (2013). Perceived usefulness, economies of scale (as related to farm size), management attitude, complementary technological infrastructure and access to finance play an important role in enabling precision agriculture technologies, while market requirements and harvest optimization appear to be key drivers of the use of automation technology.

Increasing crop yield and profit optimization remain at the heart of commercial farming, and the decision to adopt precision agriculture technologies comes in support of this goal (Barnes et al.,2019; Kolady et al., 2021). The involved economies of scale and the adoption challenges faced by smallholder farmers (especially digital platform access and high data costs) underscore the importance of coordinated policy and the role of affordable complementary infrastructure in fostering inclusive technology diffusion, as argued by Aguera et al. (2020) and Kudama et al. (2021).

The deployed technologies, rather than being disruptive, seem to have contributed to strengthening the performance of the agricultural industry in its existing markets. The deployment of a locally developed digital agriculture technology in some sub-sectors provides the advantage of technological tools directly adapted to their needs and appropriate for the intended tasks. It also provides its users with certain levels of autonomy, in contrast to the type of dependence on powerful foreign technology platforms that often dominate the smartification of agriculture (Wolfert et al., 2017; Zhang, 2015). Easy access to a certain technology is also a good predictor of its adoption and potential diffusion, as observed by Gabriel and Gandorfer (2023) in the case of digital technology adoption among farmers in Bavaria.

Regarding the perceived ease of use, it is of particular importance to bear in mind the distinction between precision agriculture technologies with mostly embodied technological knowledge and those that are information intensive. Information-intensive technologies require additional skills to optimize their application and usefulness, while embodied precision agriculture technology embeds most of its functions as automatic, thereby requiring less effort in utilization. The latter are therefore more easily adopted (Pierpaoli et al., 2013; Kolady et al., 2021; Miller et al., 2019).

In conclusion, the observed outcomes in terms of labour productivity increase, skills development, improvement in crop quality and yields as well as the positive spillovers for environment sustainability indicate a positive role for digital technologies in confronting the challenges posed by water scarcity and the effects of climate change in South Africa. Our findings highlight the importance of economies of scale in technology adoption decisions, due to high cost involved in adopting many of the advanced technologies focused on in this study. Many small-scale farmers consider these technologies as prohibitively expensive: a meticulous coordination of their resources through industry associations and government support remain essential to broadening their chance to access these technologies. Moreover, a constant collaboration between the government and industry players is indispensable for creating favourable conditions for large as well as small players to thrive in their respective businesses and thereby contribute to the country’s economic dynamism.

These findings also highlight the importance of fostering digital inclusion among farmers as a measure to increasing their visibility in the wider value chain (see also Kudama et al., 2021 and Aguera et al., 2020). Access to digital infrastructure networks being one of the limiting factors, policies aimed at strengthening the diffusion of advanced technologies in the sector should focus on improving the coverage and affordability of such infrastructure throughout the country, as well as supporting digital skills training and capacity building among prospective adopters. The problem of affordability of some advanced technologies, such as the use of UAVs and satellite imagery mentioned by some respondents, requires closer policy coordination and land reform acceleration to ensure that more producers reach the level of scale and skills that would enable them to make profitable investments in the adoption of such technologies. Such support should ideally give priority to smallholder farmers, including through the development of shared technology services that help them overcome the constraints of scale that render outright purchase of technologies prohibitively costly.

As a final point, the use of digital technologies is not without risks, especially when part of the technology services is controlled by powerful private corporations handling proprietary data generated through technology utilization. Consequently, data protection with adequate regulations ought to be central to technology use, in order to protect small-scale farmers from the related vulnerabilities when they choose to adopt digital technologies connected to private platforms. The development of alternative technology support services with the necessary adherence to local regulations could be explored to improve the bargaining position of technology adopters.

Declarations

Ethical declaration

Ethical clearance for the project was granted by the Ethics Committee of the University of Johannesburg under Ethical Clearance Code: 21SECO036. Th research was conducted in accordance with the ethical guidelines of the research ethics guidelines of the University of Johannesburg. Respondents were asked to consent to participating in the interviews as well as to accept to be recorded for the purpose of keeping records. They were promised confidentiality and anonymity in the treatment of the recorded data, intended to be used only for the purpose of analysis.

Disclosure of conflict of interest

No potential conflict of interest known to the authors.

Artificial intelligence declaration

No artificial intelligence tools were used neither in the research nor in the drafting, analysis and validation of this study.

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Author Contribution

The authors confirm contribution to the paper as follows: Study conception and design: A. Habiyaremye, P. Ncube; Background and literature review: A. Habiyaremye, P. Ncube, A. Slater, K. Sichoongwe; Methodology: A. Habiyaremye; Data collection: A. Habiyaremye, P. Ncube, A. Slater, K. Sichoongwe; Interview transcript review: P. Ncube, A. Slater; Formal analysis and interpretation of results: A. Habiyaremye, P. Ncube, A. Slater, K. Sichoongwe; Draft manuscript preparation: A. Habiyaremye, P. Ncube, A. Slater, K. Sichoongwe. All authors reviewed and validated the results and approved the final version of the manuscript.

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Data Availability

Due to the confidentiality of the collected information, the supporting data cannot be made publicly available. However, the data can be made available upon reasonable request. To comply with the editor's request, we supply the anonymised interview transcripts as well as the interview guides for the purpose of peer review. This information should not be used for any other purposes.

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Footnotes

1. The agriculture sector contributes only about 5% of formal employment and 2.5% of GDP but forms the basis for the agroprocessing value chain and is essential for the country's food security and export revenue (Nedbank, 2024).
2. Depending on the size, colour and appearance of the fruit, the machine decides, for example, whether the fruit will be sent to China or Europe, which box it should be in and which packaging size it should be conditioned in.
3. The interviewed respondents do not deal directly with the consumers in communicating the production processes, but they discuss the consumer sustainability preferences through connected retailers.

Figures

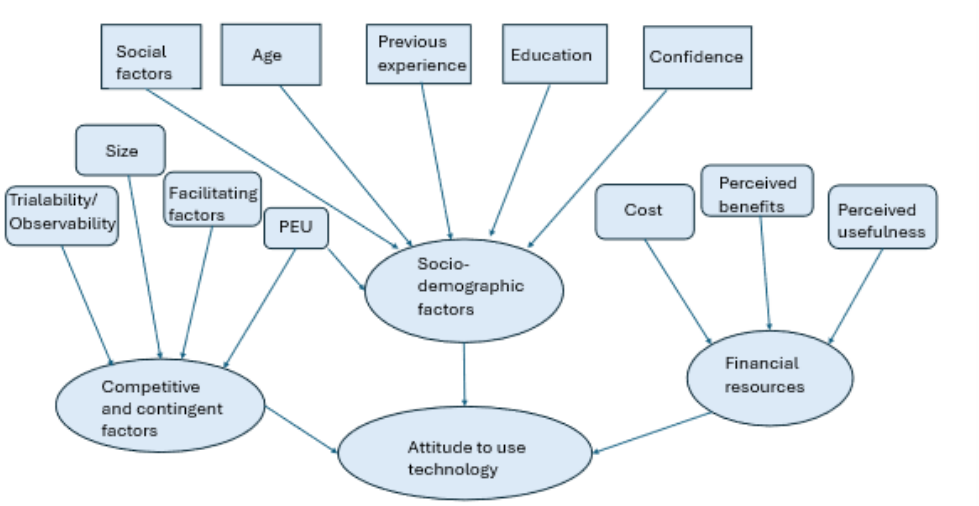


Figure 1

Ex-ante factors affecting attitudes to using PA technologies

Source: Adapted from Pierpaoli et al. (2013)

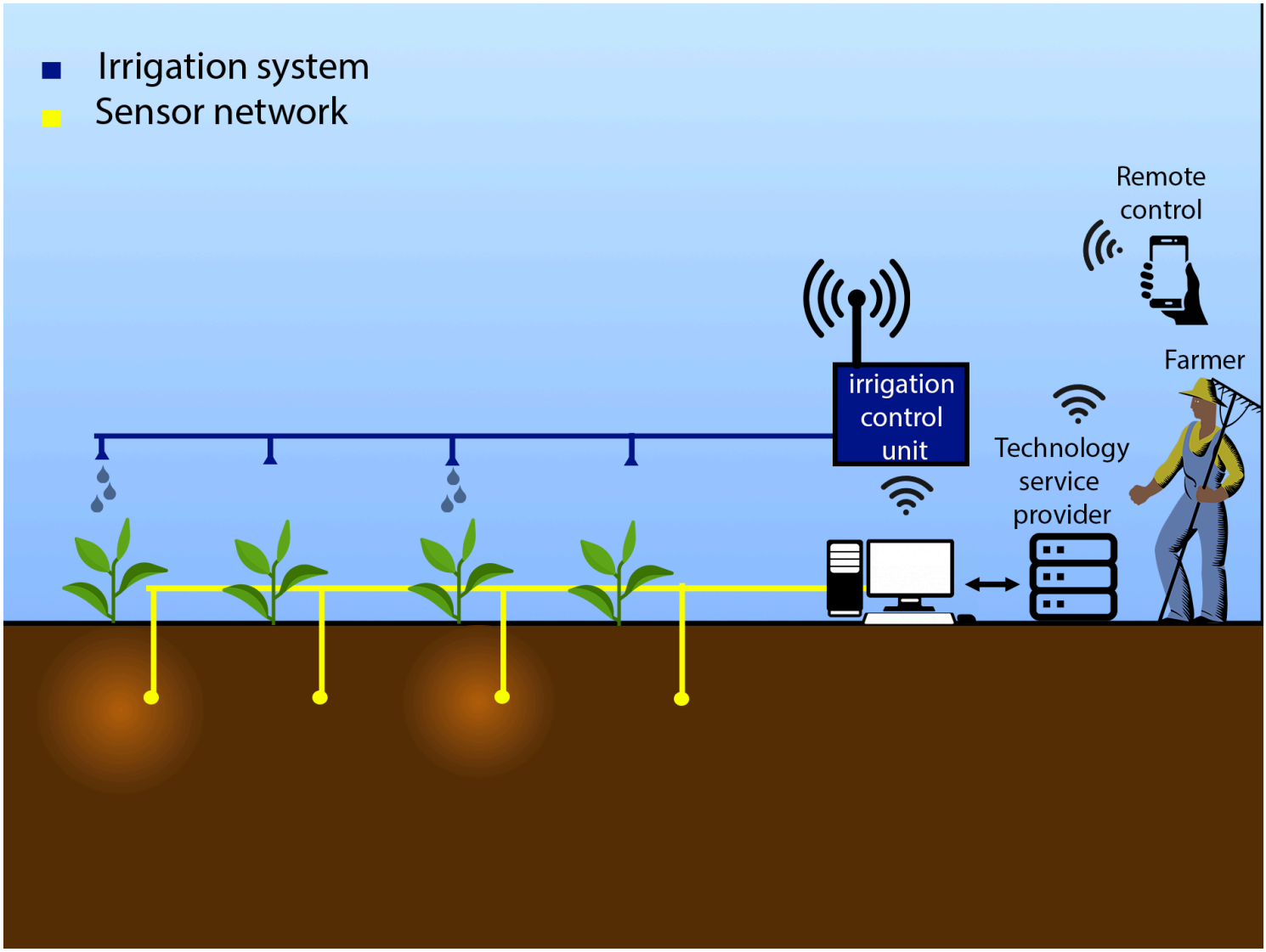


Figure 2

Schematic representation of the FarmNode automated irrigation module

Source: Sketch by R. Habiyaremye