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Research Article

Automation and AI in US Agriculture: Revolutionising Farming through Smart Technologies and Farm Management Software

Muhammed, Usman[1] and Adebayo, Adedeji[2]

[1]*Department of Agricultural Engineering, Federal University of Technology Akure*
[2]*Mechanical Engineering Department, University of Ibadan*

Abstract

The US agricultural sector is undergoing a significant transformation driven by automation, artificial intelligence (AI), and smart technologies. These advancements fundamentally reshape traditional farming practices, enhance efficiency, and promote sustainability across various agricultural domains. This paper explores the integration of AI-driven technologies such as drones, sensors, farm management software, and robotics, which have revolutionised crop and livestock management by enabling real-time data acquisition, precision farming, and automated processes. Despite the numerous opportunities offered by these technologies, the agricultural industry faces significant challenges related to high implementation costs, technological accessibility, and the need for tailored training programs. Furthermore, the economic implications of adopting these technologies, including potential labour displacement and the necessity for new skill sets, are addressed. Through an analysis of current practices, this paper highlights the potential of AI and automation to improve productivity and environmental conservation while considering the social and economic hurdles that must be overcome to achieve widespread adoption.

Keywords	*Artificial Intelligence; Precision Farming; Smart Farming; Farm Management Software; Revolutionising Farming; Livestock Monitoring; US Agriculture; Smart Technologies*
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Introduction

Agriculture represents a vital domain of the US economy (Sharma et al., 2022). Cultivation practices are slowly embracing intelligent technologies, and thus a revolution is happening in American farming (Wang et al., 2021). Smart farming consists of the use of modern equipment and robotic technologies that are designed to serve a particular purpose that was inaccessible within a traditional approach. Drones are now implementing modern farming strategies by generating maps for more accurate sowing (Javaid et al., 2022). Nevertheless, drones represent only one particular example since we can discuss many more tools and systems; literally, all can affect the development of smart farming. Robotic systems aim to diminish the workload in agricultural robotics (Charania & Li, 2020). Farming Management Software results from all these upgrades and can provide a significant amount of help to farmers. A quick move towards adopting these new tools fundamentally enlarges the influence and efficiency of applied strategies, leading to the rise of overall agricultural production. The challenges of traditional agriculture are numerous and complex to fight. Their situation is even more complicated nowadays due to the exponential increase in population, directly affecting the amount of food people require.

Along with this increased need for food comes the requirement for an increasing number of sustainable management strategies to deliver food to society. Each tool approaches the challenges step by step and virtually unites efforts in feeding humankind. Encompassing all of these is the same objective, with each decision contributing to the overall impact of mitigation strategies for the hunger of developing nations. Delivery of crops relies heavily on cost-effective methods that assure, as best as possible, an environmentally friendly attitude. This work objective integrates a set of strategic methods that address this issue, conferring an essential level of relevance. As efficient and modern technologies like artificial intelligence and automation provide critical information and expand the decision-making process, this text tends to unify various methods concerning their influence on US agriculture and rural families that generate the needed information for society and competent decision-makers. The need for research investment regarding modern farming technologies concludes and offers a broader range of developments at the scientific pace and, even more importantly, at the social pace.

Background and Significance

Throughout history, agriculture practices have adapted to introducing and streamlining new technologies (McFadden et al., 2023). However, until the last century, the processes that define agriculture today—tillage, sowing, and harvesting—remained unchanged. Integral to food production, these stages have experienced significant innovation in the last thirty years, leading to increased yields, sustainable pack-down, and other benefits (Bazargani & Deemyad, 2024). Automation is the practice of reintroducing these processes safely and efficiently, with the higher precision required by the farmers for whom this technology is designed (Karunathilake et al., 2023). Today, almost one-third of the world's crops are harvested mechanically out of necessity, owing to labour costs. The potential exists to expand this figure exponentially, aiding global food security and sustainability as a combined strategy, lessening the strain on the Earth's agricultural land and negating the need to expand further into biosphere reserves (Gil et al., 2023).

In this context, an area of real significance is outlined: the threats to food production and environmental practices linked to labour supply, both quantity and suitability, for rural cases. An increasing urgency exists to address the rising labour costs and accessibility issues that threaten the economic viability of non-mechanised, wholly manual pickers. At the global scale, while agricultural labour supply is all but endless in some countries, in others, an already perilous workforce situation is exacerbated by an ageing rural population, leading to shortages and preventing ambitious expansion. The popularity of urban living is likely to worsen in the future. Carefully piloted automation efforts to address real-world capacity constraints driven by labour accessibility or environmental concerns are significant. Fundamentally, automation drives efficiencies and, along with other smart technologies, allows farmers to capitalise on the world's continually rising demand for bulk herbs, fruits, vegetables, and other classic manually harvested crops. Automated fruit picking can be used in response to bulging labour demand, thanks at least to the fact that each harvester enjoys the most premium crop quality.

Scope and Objectives

The scope of this work is farming. Farming, or agriculture, raises livestock and crops to produce food and materials. This process requires many activities that could be categorised into two main groups: crop management and livestock

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management. This work aims to only look at farming technologies in the US, concentrating on livestock and crop/horticulture farming management. The study develops from the idea of looking at the benefits of the application of smart technologies and farm management software based on individuals' practical farm experience and literature available on the topic of automation in US agriculture.

This study aims to highlight various types of technologies available, determine whether these automation and AI technologies were a valuable investment for farms, and identify a selection of existing and potential implications for the farming entities reviewed and industry shareholders where they are relevant. It is essential to review and evaluate whether automation and AI in farming are worthwhile. To do this, the following questions must be addressed: What types of automation are currently available, and what future advancements could be developed? It is also essential to determine if implementing intelligent technologies is a worthwhile investment, so questions are addressed about the benefits and challenges that must be overcome.

Historical Evolution of Automation in Agriculture

The mechanisation era began in the early 1900s and marked a major agricultural revolution as farming transitioned from manual labour to using tractors, combine harvesters, and irrigation systems. By 1900, with a global population of 1.6 billion, each farmer fed about 10 people, relying heavily on manual labour. However, by 1950, with the introduction of farm machinery, including tractors, each farmer could feed 27 people, supporting a population of 2.5 billion (Mahmud et al., 2020). These technological innovations significantly transformed modern agriculture, shifting from the peasant mode of production to a more mechanised system (Kim et al., 2020). As seen by 2000, further advancements in mechanisation, such as advanced machinery and online data systems, allowed each farmer to feed 130 people, contributing to a global population of 6 billion. This shift from manual to precision farming has revolutionised agricultural practices, increasing efficiency and yields while enhancing profitability (Aiello et al., 2022). By replacing manual labour, mechanisation has significantly boosted productivity and output, improving farm profitability (Hansen et al., 2020).

The agriculture sector is progressing towards smart farming, integrating data management systems that collect, manage, analyse, and disseminate information to aid in field-level decision-making, reduce costs, and conserve resources (Kim et al., 2020). Past developments in automation have led to self-adjusting machines and sensors that enhance precision in farming processes. This ongoing shift leads from traditional machinery-based farming to autonomous systems, including greenhouse robotics, which are rapidly advancing and capable of doubling yields while conserving water and reducing pesticide use (Aiello et al., 2022). By 2030, with the global population expected to reach 9.7 billion, intelligent technologies, including artificial intelligence (AI), weather predictability tools, and geographic information systems (GIS), will be crucial in feeding the growing population efficiently. Automation in agriculture has improved working conditions and product quality and raised questions about the future of skilled labour and the socioeconomic impacts of shifting labour markets to urban areas (Hansen et al., 2020). While self-adjusting and self-learning machines enhance productivity, they pose challenges in determining how decisions are made and who controls them, creating new complexities in agricultural paradigms (Mahmud et al., 2020).

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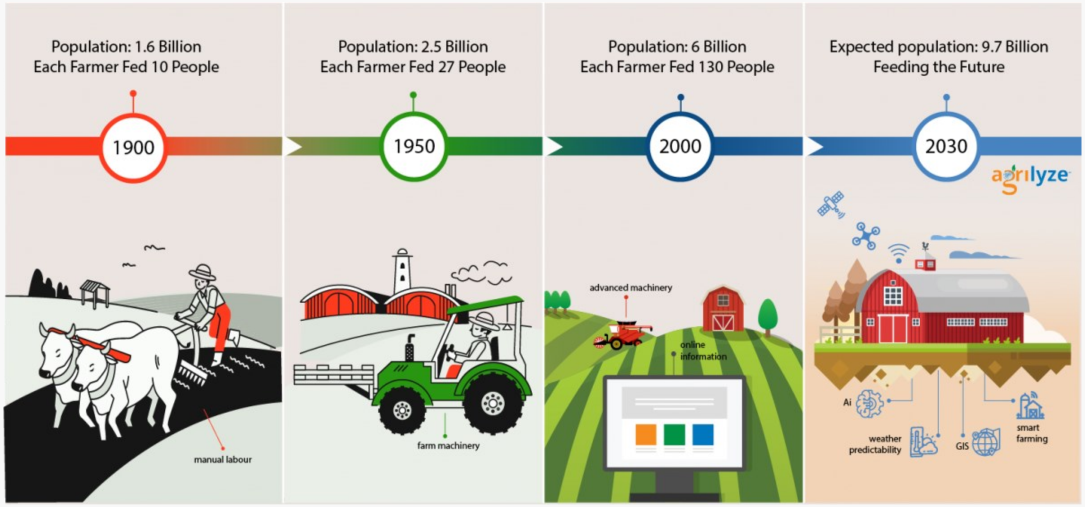

Figure 1: Evolution of Farming Technology

Mechanisation Era

The introduction of machinery has dramatically sped up food production and lowered consumer costs (Hemathilake & Gunathilake, 2022). The tractor invention allowed crops to be cultivated and harvested with large machinery so that a single farmer could plant, cultivate, and harvest more acreage than possible with a team of horses or labourers. Farming, as it was known at the time, included labour that had to be performed by hand; there was so much physical human labour required that it put a strain on available labour. In the past, large, expensive machines like combine harvesters were only made to service the most significant operations. However, that has changed with the advent of computers built into farm machinery. Resource-poor farmers can now buy land and use equipment and science to farm more extensive areas, thus cutting the cost of food (Raj et al., 2022). The change was so profound that it affected how farms were managed and crops rotated. It used to be that most people were farmers. Now, only about one or two out of every 50 people can call themselves farmers—many of these are more than small business employers (Baur & Iles, 2023). As tractors and machinery took over the work usually reserved for harried labourers, most left the farms, started working in country stores, and then commuted to the city for factory jobs. As rural labour has deteriorated and younger people go to the city for work, rural communities have had to think about new ways to get jobs for young people and keep their neighbourhoods from becoming completely deserted (Hemathilake & Gunathilake, 2022).

Precision Agriculture

Precision agriculture (intelligent agriculture, site-specific crop management) is a farming management concept based on observing, measuring, and responding to inter- and intra-field crop variability using information and communication technologies (Bolfe et al., 2020). It was adopted from traditional broad-acre farming. However, it has become popular to use efficient soil testers and crop yield monitors for fine-tuning interventions to match soil-specific nutrient supplies and reduce waste (Balafoutis et al., 2020). It also seeks to ensure profitability, sustainability, and protection of the environment through resource management and mitigation of the environmental impact of agricultural waste. The adoption of precision agriculture has the potential to increase yields and make the crop and farming system of the future more sustainable (McFadden et al., 2023). Precision agriculture has been driven by technological advances in data collected from remote and proximate sensors such as global positioning systems (GPS), sensors to measure soil conditions, crop yields, and yield monitors for discussing the vast amount of granular data available to farmers, along with software analytics for making field metrics out of this data (Khanna et al., 2022). Data from remote-sensing instruments can provide information that can assist farmers in making smart decisions, including information about crop biomass, crop health variables, and many useful indices derived by combining sensor wave bands (Charania & Li, 2020). For example, plants depend entirely on soil moisture to raise seeds and fully develop.

Balancing soil moisture (water) and fertiliser availability throughout the growing season, depending on the crop's demands, requires intelligent decisions, which are possible with sensors and by applying precision agriculture technologies (McFadden et al., 2023). Lower crop risk and increasing farming sustainability generally make efficient use of resources that are accessible to manage. These aspects are a fundamental commitment to precision farming tools and technologies. Most of the advantages of precision agriculture practices lie in management staples. The use of technologies to aid in decision-making rationalises the requirement for human resources (Bolfe et al., 2020).

Additionally, using digital communication, pH meters, and GPS makes precision agriculture a time-sensitive operation. Real-time applications are helpful in areas like monitoring crop health and equipment tracking. The problematic nature of the technologies while they are in the field under our command compels on-the-spot trained personnel to deal with emergent breakdowns and routine maintenance (Khanna et al., 2022). Some retailers offer e-commerce solutions for purchasing precise agricultural equipment and software as 'off-the-shelf' solutions.

Most farmers across the United States have already integrated technology and automated processes at an increasing rate into their operations, especially working with farm management software (McFadden et al., 2023). Deploying field management software or data analytics in agricultural production implies saving money while obtaining top performance in crop yields. US farmers have adopted precision agriculture at a growing rate, utilising GPS, standard among two-thirds of Iowa farmers and farmers in Indiana, Illinois, and Kentucky. From steering guidance systems to GPS yield monitoring systems, Ohio, Michigan, Washington, Texas, and South Dakota farmers have shown increased interest in having this technology in their operations (Charania & Li, 2020). Currently, we find that 13 million US farms have utilised this technology to grow crops that top an aggregate value of over $100 billion. In Georgia, farmers indicate that field management software is as significant to their operations as GPS yield monitoring systems. This software enables real-time, current, and past data analysis while generalising how the crop has been performing on the farmer's fields in terms of yield on the farmer's computer. With just a few clicks on the keyboard, a farmer benefits from time-saving information (Balafoutis et al., 2020).

Foundations of Automation and AI in Agriculture

Multiple technologies have gained traction in the agricultural sector in the past decade. These include IoT, automation (in the form of robotics), and AI (in terms of machine and deep learning) (Charania & Li, 2020). These are chosen because they provide the precise and time-appropriate actions necessary in agriculture. The driving force behind these technologies in agriculture is the ease with which data can be collected. These sensors can monitor the growth of individual plants, drones that can cover vast areas, manifold data sources, and the vast scalability of what we can achieve (Bhattarai et al., 2020). Large-scale data collection allows for vast datasets containing enough indexes to classify in faint granularities or for AI-based models to be more robust. This can help in tasks such as:

a. Weed removal: The robot can differentiate crops from weeds, remove the latter, and apply herbicides only to occurring vegetation.
b. Thinning: Remove excess plants to allow for a higher yield on unaffected ones.

Modern industrial agricultural equipment enables farmers to monitor different climate conditions. Farmers can also collect their intrinsic plant characteristics (traits) from sensors and multidisciplinary sources as robust digital measurements (Baur & Iles, 2023). Farm management software can also provide a prognosis for the future and optimisation based on past experiences. Data is consequently stored and aggregated, and the feedback loop can further be extended via analysis in a broader scope, such as crop prediction, profitability, optimisation of work routes, and inevitable fixed decisions on the fly. In conclusion, all the data from each collected aspect is combined to understand the system and its dynamics better, which can result in better decision-making (Charania & Li, 2020).

Key Technologies

The modern approach to agriculture and farm management increasingly leans on cutting-edge technology. Many technologies are advancing the frontier of automation and AI in agriculture, making farming practices more sustainable. Some of the technological innovations that are currently changing the framework of agriculture worldwide are the use of drones for field data acquisition, soil moisture measurements, and planting applications; the spread of sensors and IoT devices for hyper-detailed farm monitoring; and building on electronics, the development of modern precise guidance systems enabling tractors to move autonomously (Caicedo et al., 2020). Robotics in

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agriculture also improves efficiency in multiple application fields while reducing the need for human intervention (Javaid et al., 2022). On the science side, implementing machine learning, a subset of artificial intelligence, specifically reinforcement learning, provides many advantages of deep learning models in developing a more precise ML/AI approach, resulting in more refined decisions (Hrustek, 2020). A major revolution has come from real-time weather observations, a technology capable of compensating for the limits associated with long-term climate predictions and climatic trends in agriculture (Jew et al., 2020). Societal gains are developed potentially to produce more reliable and consistent crop yields, pest prevention, limited use of heavy machines, and water conservation, which are some applications revealing the factual potential of AI and IoT-driven agricultural practices (Sott et al., 2020).

Various advanced farming and crop management technologies have emerged and are being tested or used regularly. The advancements have happened in soil monitoring, field scouting for pests, diseases, and stressors, monitoring and estimates of crop acreage, yield, and price, and daily weather forecasting. Collectively or individually, these technologies have been affecting crop yield and quality, farm marginal profits, and season-length variability (Javaid et al., 2022). For instance, daily weather forecasting decides the best time to plant crops, purchase crop insurance, or for field irrigation and farm inputs (Scott et al., 2020). Uniform or precise applications of nitrogen and agrochemicals have become possible due to the precise information on soil characteristics based on soil sensors (Jew et al., 2020). These farming technologies combine GPS and IoT hardware to enable fast data collection, storage, and analysis of high throughput data and produce models for better decision-making in the field (Caicedo et al., 2020). This combination of various technologies has led to the development of unique farm management software and machine-learning models (Hrustek, 2020). These trends will continue to increase due to R&D on technology, labour scarcity and population, growing consumer awareness of food production practices, tastes, price sensitivity, climate change, more volatile markets, and unpredictability (Javaid et al., 2022). Challenges in adopting the described market or commercial technologies are high capital costs, unavailability or expensive labour for specialised tasks, technical knowledge and skills needed to set databases and production models, machine learning models, marketable software, and analytical skills (Sott et al., 2020). Table 1 shows the key technologies mentioned and their practice in the United States:

Table 1: Key Technologies Mentioned and their Practice

Key Technology	Description	Current Practice in the United States
Drones	Used for field data acquisition, soil moisture measurements, and planting applications	Commonly used in crop monitoring, precision spraying, and field mapping (Caicedo et al., 2020)
Sensors and IoT Devices	Provide hyper-detailed farm monitoring, soil and plant condition analysis	Widely used in soil monitoring and environmental control systems (Sott et al., 2020)
Autonomous Tractors	Precise guidance systems enable tractors to move autonomously	Gaining traction in large-scale farms, especially for crop planting and harvesting (Caicedo et al., 2020)
Robotics	It improves planting, weeding, and harvesting efficiency and reduces the need for human intervention.	Used in automated harvesting, especially for crops like berries and vegetables (Javaid et al., 2022)
Machine Learning (ML) and AI	AI-based systems for decision-making in precision farming, pest control, and crop health	Implemented in predictive modelling, yield prediction, and pest detection (Hrustek, 2020)
Real-Time Weather Observations	Compensates for the limits of long-term climate predictions	Used in forecasting crop cycles, irrigation schedules, and insurance decisions (Jew et al., 2020)
Field Scouting Technologies	Monitors for pests, diseases, and stressors	Deployed on larger farms for real-time crop and pest monitoring (Javaid et al., 2022)

Soil Monitoring Sensors	Measure soil characteristics for precise nitrogen and agrochemical application.	Applied in nutrient management and irrigation systems to improve yields (Jew et al., 2020)
GPS Integration	Enables precise location tracking and data collection	Standard in farm machinery for field mapping and automated guidance systems (Caicedo et al., 2020)
Farm Management Software	Combines data from various sources to improve decision-making	Used extensively in crop management, inventory tracking, and yield forecasting (Hrustek, 2020)
Automated Calving Detection	Uses AI and sensors to monitor livestock during calving	Deployed on large dairy farms for early detection of calving and health monitoring (Avizheh et al., 2023)
Early Health Monitoring Systems	Monitors animal health through wearable devices, increasing milk yield	Used in dairy farms to enhance milk production and manage herd health (Keceli et al., 2020)

These technologies represent diverse innovations incorporated into modern agriculture in the United States, particularly in large-scale commercial farming, where automation and precision agriculture tools are increasingly essential to improving productivity and sustainability.

Data Collection and Analysis

The vehicles and systems described in the previous sections are all data-driven: their ability to make their original tasks more efficient and precise relies on the quality and accuracy of the information they receive (Bousdekis et al., 2021). This encompasses everything from how quickly a vehicle moves through a field and in which direction to assessing the crops' growth, health, and water and nutrient needs (Wu et al., 2021). There are several ways to collect this data about a given field and its plants. Various sensors can monitor and provide real-time information about the state of soil and plants. Satellite and airborne imagery provide field weather data and are increasingly used for pattern and anomaly detection (Chen et al., 2020). At the farm management level, strategies and decisions are increasingly being informed by using farm management software (Kaiser et al., 2021). The range of data that can be captured this way includes grower-timestamped field operations, as-planted and yield data, rainfall and soil moisture, and the resultant field responses. The data can be analysed using advanced analytics, artificial intelligence, and machine learning to provide insights into plant growth, soil condition, the influences and correlations with the interplay of different agronomic variables, ongoing environmental impacts, and the potential for outcomes under different scenarios (Chen et al., 2020). Thus, the data, their analytics, and the insights that can be generated all have different interpretations and implications, dependent on the context in which they are being used. Real-time data allows monitoring and prompt management decisions and responses to changing farm conditions (Wu et al., 2021). Data-driven analytics provide insights supporting predictive modelling and planning for future scenarios (Kaiser et al., 2021). Large-scale datasets and analytics can also provide broader holistic insights. Enormous challenges remain in managing, analysing, interpreting, and acting upon large datasets and translating the generated insights into actions (Bousdekis et al., 2021).

Applications of Automation and AI in US Agriculture

Over the past decades, there has been a revolution in US agriculture primarily driven by precision farming techniques and the availability of large and high-dimensional data (Baur & Iles, 2023). Precision farming has been applied in many agriculture sectors, including plant and animal production processes, and for many different crops worldwide (Lenain et al., 2021). A central aim of implementing these technologies in farming is to increase the field's and value chain's efficiency, particularly in resource management. Crop production has been done mainly to manage fertility, pests and diseases, precision irrigation strategies, and site-specific harvesting (Rondelli et al., 2022). In animal husbandry, technologies have been applied for livestock monitoring, with the primary objectives being animal health management, production optimisation, and welfare (Lagnelöv et al., 2021). Weed and pest control technologies use chemical, mechanical, or biological systems or combine precision management of crops with autonomous control systems. They offer the possibility to reduce the use and concentration of pesticides or improve their efficacy (Ghobadpour et al., 2022).

The US agriculture industry has started working with autonomous tractors since 2017. American farmers are considered early adopters of autonomous systems and have a competitive advantage with the quality of machines made in the US. The first self-driving tractors were used for pinpoint planting of crops such as corn and soybeans (Baur & Iles, 2023). In 2020, digital farming technologies emerged in the US to obtain data analysis for better efficiency in the field and during post-harvest planning (Lenain et al., 2021). Intelligent technologies such as the autonomous grower feeding system are used in the livestock sector in the US. Eighty-two per cent of poultry and ninety-five per cent of pork are produced in the US with the support of robotic farming (Rondelli et al., 2022). Concerning reducing chemical fertilisers and pesticide use, the government has promoted sustainable energy for reducing tractor inputs (Ghobadpour et al., 2022). In the US, robotic and AI tools support Olympic gold medal farmers in producing, in a minimal space, from 10,000 to 40,000 pounds of local vegetables and herbs. In crop management, technologies are being developed to manage chemical inputs in fruit production, pesticide applications, field management software, greenhouse and nursery licensing, etc. In the US, automated production of high-quality mushrooms has seen exponential growth of 20–30% for the next five years. Large investors are buying mushroom farms to develop state-of-the-art entrepreneurship with the help of automation. Major mushroom farms are adopting automation to help produce high-quality mushrooms and cut costs to remain competitive (Lagnelöv et al., 2021). AI is used for pricing, scheduling, yield prediction, yield optimisation, quality management, robotics, and engineering behind mushroom production (Rondelli et al., 2022). AI in mushrooms uses diverse data types, including pictures, text, and videos. AI is mainstream in the domain of mushrooms. US mushroom farms are not regulated and operate locally to exploit a growing market in recipes and low-calorie food (Baur & Iles, 2023).

Precision Farming

Precision agriculture, also called precision farming, is a concept that appeared in the United States in the 1980s (Yang, 2020). It means precision or diverse cropping, and it aims to modify crop management content to suit all crop management objectives by using new technologies such as data collection and processing, including location awareness and geographic information systems (Sishodia et al., 2020). Precision agriculture is a technical system that can manage environmental factors and spatial variability in crop fields' soil and environmental conditions (Monteiro et al., 2021). Dysfunction in providing data for crop-growing models includes watering systems that can be managed efficiently and precisely. Precision farming operations are conducted according to the principles of communicating the actual needs of crops and natural soil. GPS is among agriculture's new production technologies that can measure the Earth's surface, including soil, water, land, forests, and farm boundaries, and can mark the location of precision farming for individual agricultural units (Nowak, 2021).

This technology is compatible with digital mapping, remote sensing, inspection of soil samples, and new geostatic module equipment. Central and local natural resources include fertiliser fields, plastic fields and applications, organic waste, and pesticides. There is no broad consensus among researchers on the basic principles of precision farming, but the concept includes the establishment of complete uniformity in managing fields from mass analysis (Sishodia et al., 2020). Although precision farming is not yet universally applicable, there is a case where increasing yield up to 3,537 tons per 16 tons per hectare increases fertiliser levels in soil mapping fields (Monteiro et al., 2021). The results will benefit farmers and the technical environment to mitigate the damage caused by repeated administration, such as hiring a semester increase. Thriving precision agriculture can also help reduce water and fertiliser consumption in agriculture and minimise its impact on the environment (Yang, 2020). In general, it can also expand the scope of the farm because it can recover damaged acres of land (Nowak, 2021). There are still obstacles that must be overcome when applying precision principles in agriculture. Some require faster technology, more reasonable costs than technological tools and software, and property rights for the safe and stable use of hardware (Sishodia et al., 2020). At the same time, research must support the industry in applying appropriate technologies that improve existing and new technologies and field management. Precision agriculture will support changes in agriculture, which are increasingly based on concentrated agricultural land, technology, and applications (Monteiro et al., 2021). In addition, the principle of fairness is related to traditional agriculture, which is more profitable and develops as a basis for pilot, greenhouse, and ornamental specialities and urban farming that can provide profits. In short, this agricultural advance

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uses the latest gadgets, combines tradition with innovation, and is committed to sharing the responsibility of reducing greenhouse gas emissions (Nowak, 2021).

Livestock Monitoring

Effective livestock monitoring is expected to improve health, productivity, and resilience through AI (Keceli et al., 2020). It can ensure real-time animal health and welfare monitoring, providing farmers with feed and time management benefits. Some of the real-time monitoring employed for livestock uses activity tracking devices (Avizheh et al., 2023). Smart ear tags and rumen boluses have been developed for cattle, communicating with mobile devices to provide livestock location, temperature, or other health indications. Drones can be used for inspection, herding, or monitoring to develop a picture from the air to keep track of the animals (Vázquez-Diosdado et al., 2023).

Improved welfare through AI, such as predictive phenotyping, can allow earlier interventions to ameliorate health and other animal issues. This can significantly aid in situations where direct welfare or behaviour monitoring is impossible. Good feed management is essential, and this can be improved through learning algorithms that assess genetic background or microbiota data in combination with food inputs and outputs (Keceli et al., 2020). Challenges include integrating with human practices for managing and interacting with livestock. However, long-term investment returns in this area are projected for appropriate animal enterprises, as with many technologies (Avizheh et al., 2023).

A calving detection tool using machine learning to analyse bovine activity, location, and other physiological data shows an accuracy rate of over 97% for farmers using the technology in a clinical study despite no prior experience using these tools (Vázquez-Diosdado et al., 2023). For feeding management, an immersive collaboration UI using various data, including animal location, movement, eating speed, weight, and other sensors, offers insights with predicted cost savings of up to 85% (Avizheh et al., 2023). A recently developed 'early health monitoring' system, using data from rumen boluses, demonstrates an increase of 1.3 kg average yield of milk per cow per day based on a trial of 300 cows (Keceli et al., 2020).

Weed and Pest Control

Automation and AI have supported rapid weed and pest control changes through high-throughput phenotyping (Adetunji et al., 2023). Machine vision is a popular method integrated with agricultural machinery systems, drones, and satellites. Thus, many phenotyping-based approaches were incorporated with AI for weed species detection and implemented as add-on systems for automated weed control (Subeesh & Mehta, 2021). Summing up the above, it is possible to state that the change in weed and pest control is a rapid process that uses high-throughput phenotyping data and associated technologies. Pests significantly threaten crop production, accounting for about 40% of all global crop losses (Adetunji et al., 2023). Sensors and robotic systems are used to observe and manage the dynamics of pests. Infestations can be challenging to close down, and many flying pests can harm many crops. By combining weather information, bot activity, temperature, and consolidation, there are plenty of ways to track and dashboard exactly how the bots are specifically contributing. Pest infestations can be difficult and costly to treat with chemicals and often need to be treated again (Subeesh & Mehta, 2021). Initial social robot costs and inexperience were barriers to entering the region, which has an increasing number of large corporate farms. Once farmers realise that they can raise premium products with fewer chemical treatments, they may be able to generate revenue. Hormones redirect mated female moths to control the fall armyworm, rapidly moving across the continent, reducing yields and threatening food security (Adetunji et al., 2023).

Challenges and Opportunities

The transition towards integrating automation and AI in agriculture presents numerous opportunities, yet farmers face considerable technological, economic, and social challenges (Bolfe et al., 2020). Access to technologically advanced machinery, farm management software, and training is still lacking in the farming sector and in tiny and medium-sized farms (Gil et al., 2023). The adoption of automation and AI is also hindered by economics, primarily because of the high costs associated with purchasing the equipment software and the need to find an adequate return on investment (Balafoutis et al., 2020). Although financial and logistical barriers are considerable, the advances in technology in the agriculture sector present reasonable opportunities to improve productivity and the overall flow of work on farms, from seeding to plant management to harvest and even post-harvest (Bolfe et al., 2020). Integrating intelligent technologies and farm management software with various machinery and materials has, and will continue to, save significant time and money in the long run (Gil et al., 2023). Moreover, these technologies can increase productivity and efficiency due to precision agriculture's more targeted and accurate approach (Balafoutis et al., 2020). The potential benefits are plentiful, but so are the challenges in realising them and securing a just transition in the food and farming sectors (Gil et al., 2023). It is essential to move away from technological determinism and understand these technological transitions in the context of a broader political economy. Policy can and should work to smooth this transition by providing the necessary support, incentives, information, and, most critically, education and training to ensure the required skills help empower farmers to adopt and use these tools to their full potential (Balafoutis et al., 2020). Cross-sector working between the relevant stakeholders is essential to overcoming these challenges and maximising these opportunities. Networking events and case-study-based evaluations are vital tools to make this issue more widely understood (Bolfe et al., 2020).

Technological Barriers

Despite offering a wealth of opportunities to the agricultural industry, the widespread adoption of automation, AI, and robotics faces significant technological barriers (Subeesh & Mehta, 2021). Available technologies suffer from high costs, limiting accessibility to large farming operations that can afford them (Sharma et al., 2022). Furthermore, revolutionary smart technologies and farm management software are often only accessible to parts of global agriculture, creating knowledge gaps as farmers across the globe are not trained to handle automated technologies and devices yet (Javaid et al., 2023). A noticeable lack of field testing and demonstrations results in a significant cushion between technological development and on-farm application. Furthermore, the performance of sensor and machine technologies is seldom validated in an actual implementation environment with end users, often leading to unrealistic system expectations from farmers (Bhat & Huang, 2021). Significantly, technology accessibility is limited by farm infrastructural diversity, including operational practices and agronomic differences across different parts of the globe, and thus, the variability of adhesive technology development is the root cause of the slow technology transfer onto real commercial farms (Sharma et al., 2022). Additionally, there is a knowledge gap among farmers that need to be addressed; an increasing number of digital products, services, and technologies currently available on and beyond the field, developed primarily for smallholder farms in emerging economies, also require a focus on individual farmer needs (Javaid et al., 2023). There is a clear need for tailored education and training programs across all agriculture sectors—focusing on farmers, technological developers, SMEs, and those in the advisory sector (Subeesh & Mehta, 2021). Working together makes it possible to drive progress, demonstrating technology potential from major manufacturers, SMEs, and farmer-focused inputs. However, there are often competing needs—with seed companies wanting potential yield increases but still focused on hearing how they improve crop performance, hence the need to be farmer-focused (Bhat & Huang, 2021). Suppose we can reduce or eliminate the barriers to technology adoption. Reinvestment in new, efficient technology will drive continued, careful increases in productivity and give a long-term sustainable future (Sharma et al., 2022). Working together allows the development of technological solutions that farming businesses understand, value, and adopt in their everyday operations. Overcoming these barriers will create a pathway to delivering sustainable solutions to farming businesses, supporting delivering food to a global population of 10 billion (Javaid et al., 2023). In short, effectively applying automation and robotics will support driving further productivity changes, embedding efficient production practices in a manner better for the environment (Subeesh & Mehta, 2021).

Economic Implications

Increased adoption of AI and automation technologies in agriculture depends on the broader economic implications of this technology adoption (Thompson et al., 2021). Smart technology applications on farms often involve an initial upfront investment cost, such as purchasing sensors, drones, machinery, and farm management software (Kong et al., 2021). These investment costs may be small or large, depending on the size, type, and level of technology the farm involves. However, provided the right conditions, technology can increase average yields, reduce costs, generate larger harvests, improve crop quality, and increase efficiency over time (Ochieng et al., 2022). Precision in agriculture may provide a much higher long-term return on investment, making us wonder why technology adoption in agriculture is so slow or, in contrast, so quick (Kendall et al., 2022). Many agricultural jobs today involve much manual labour, and while many have stated that these technologies can lead to job displacement, new job roles must emerge to manage and maintain these technologies (Ochieng et al., 2022). However, not all farmers have the same access to technology, equity, capital, or rental markets. These factors impact the investment size necessary to adopt a particular technology (Kong et al., 2021). Most American farmers are small and medium-sized family farms, and many cannot finance their projects from personal savings (Kendall et al., 2022). Furthermore, farm operators cannot invest in technology due to high interest rates or lack of investment capital (Thompson et al., 2021). Research shows the importance of an efficient credit market for knowledge or technology adoption and diffusion, as producers can always use bank loans to invest in new production mechanisms (Ochieng et al., 2022). Additionally, some farm technology projects can be financed through federal programming, such as reimbursement programs for those who invest in conservation (Kong et al., 2021).

Policymakers and business managers often believe that the economic implications of agricultural technology can lead to sustainability within the agriculture industry (Thompson et al., 2021). This includes providing enough food, feed, and fibre to meet the demands of the United States and other countries. Environmental concerns that can be addressed by adopting new technologies, from the field to the market, are becoming increasingly important (Ochieng et al., 2022). In theory, research shows that such technological investments are already generating potential production growth and better resource use in agriculture (Kendall et al., 2022). Agricultural and technology integration adoption policies should include understanding these challenges and their impact on labour markets in all sectors within the United States (Thompson et al., 2021).

Future Trends and Impacts

In the next few decades, next-generation drones, sensors, and advanced robotics that can be deployed on a large scale are expected to reshape modern farming. Only a few of these emerging technological trends have been fully realised commercially. Research and innovation in the area, before they enter food production systems, are currently being intensified because we recognise the tremendous financial and technical benefits they offer beyond what is presently possible. For example, robopackers are expected to increase potato production by 15 per cent. Others are optimising fungicide usage by more than 250 per cent, increasing nutrient efficiency by more than 200 per cent, and limiting other harms. To achieve a 20-30 per cent increase, other prototypes use innovative mechanisms for weed control and light utilisation.

Digital technologies and artificial intelligence will continue to deliver goods and decision support systems for land management, working at spatial scales unimaginable just a few years ago. They will inspire and improve the prospects of AgTech and AgScience in the near term. Downstream, decisions made by farmers, businesses, and regulators are likely to create greater crop diversification and higher yields while minimising environmental impacts. From a social perspective, greater precision and increased potential automation through AI technologies may alter the decisions made on the farm. Higher yields may offset lower employment costs, and it would be appealing to use large-scale robotics among smaller farmers who need more labour without higher returns, with doubt. The quick pace of forthcoming technologies allows alternative carbon disruptive innovation. Controllers, digital photonics, chemical-rich LED rooms, and advanced breeding methods for overlay in the dairy, growing crops, and composite vegetable mills may promote more fantastic soil and crop health and enhance the farmer's balance sheet. In the short or medium term, seeds are likely to embody photobombs that hold unique potential for enhanced field performance of crops and commercial animals while being more durable, healthier, and both environmentally and plant-growth salutary in either temperate, arid, or wet climates. Agricultural industry segments' efficiency and rapid innovation offer prospective alternatives and increase agricultural production and utilisation potential for sustainability and self-sufficiency. The only issues that technology and innovation do not solve are volatility and resilience, which are issues that, if anything, can be exacerbated by innovative technologies.

Emerging Technologies

Emerging technologies are revolutionising traditional agricultural practices, paving the way for smarter solutions for monitoring and managing farms and crops. Some emerging technologies included in this study are drones with multispectral, hyperspectral, and LiDAR cameras, autonomous or semi-autonomous vehicles, and machine learning-based monitoring and yield prediction applications. Drones with multispectral and hyperspectral cameras allow for spectral monitoring of farming activities, while LiDAR scanners enable crop 3D monitoring. Autonomous or semi-

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autonomous vehicles enhance the efficiency of farming activities through reduced input applications. Machine learning applications allow for intelligent and efficient management of the farm.

Research studies show the potential of these technologies in enhancing various parts of smart agriculture, including monitoring, early detection, yield prediction, disease monitoring, water use efficiency, productivity, and profitability. Some technologies move toward the autonomous application of the developed methods, while some are limited to research tasks. These technologies require further research to move from research to commercial application. However, these technologies present significant challenges related to adoption, including poor data access, lacking computational capabilities, infrastructural capacities, and social and psychological acceptance. The interaction of developed smart technologies with current practices has been undertaken to understand where these technologies are placed within the farm. Education on how a farmer can interpret the information technology provides is needed to increase the application of advanced technologies in agriculture. Some individuals argue that automation and traditional or semi-automated agriculture are entirely different concepts, as they have different goals. Automation in farming should be equipped with training and maintenance through software applications. The following subsections illustrate some of the technologies mentioned earlier alongside their applications to real-world problems.

Socioeconomic Effects

The increased productivity and efficiency gained from the introduction of automation and AI in farms can significantly affect the socioeconomic environment of US farming. Likewise, increased productivity allows small-scale farmers in different parts of the world to continue to grow and provide rights to underserved populations, leading to better farm management. However, automation and artificial intelligence capabilities that computers can improve or replace human abilities affect labour requirements in agriculture. While technology can change the type of job and the amount of labour required, it also leads to job displacement due to equipment redundancy. Adding layers of advanced technology and data creates an even more technologically advanced need for human capital, emphasising that marginal access to resources like planting technology or robotics is a problem for small farms. New knowledge about professionalism is also a concern for farm workers who lack resilience. These innovations are often more likely to occur in large and advanced farms that employ sophisticated professionals and experts. As a result, rural economic systems with more small-scale farmers and underdeveloped communities can shift to a declining competitive position in efforts to achieve economic and personal goals. This change in the socioeconomic position of large and small farmers can affect the equitable and resilient communities needed to meet future food needs and the success of communities in promoting economic development and additional revenue strategies. While these automated and intelligent farming functions are generally considered beneficial, there are potential social and ethical problems. These should focus on taking advantage of evolving agricultural automation and artificial intelligence technologies and ensuring social fairness in food security beyond the changes in farming culture and the integrity of the fields. Empowering society to develop the necessary policies, ensuring barriers are in place, and competing or using technologically oriented rural communities is essential. The federal government argues that people who lose or change their jobs need additional assistance and training to become self-sufficient. Research would, therefore, be necessary to identify overlapping areas of emergency action.

References

Sharma, V., Tripathi, A. K., & Mittal, H. (2022). Technological revolutions in smart farming: Current trends, challenges & future directions. Computers and Electronics in Agriculture. [HTML]

Wang, T., Xu, X., Wang, C., Li, Z., & Li, D. (2021). From smart farming towards unmanned farms: A new mode of agricultural production. Agriculture. mdpi.com

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. International Journal of Intelligent Networks, 3, 150-164. sciencedirect.com

Charania, I. & Li, X. (2020). Smart farming: Agriculture's shift from a labor intensive to technology native industry. Internet of Things. [HTML]

Karunathilake, E., Le, A. T., Heo, S., Chung, Y. S., & Mansoor, S. (2023). The path to smart farming: Innovations and opportunities in precision agriculture. Agriculture. mdpi.com

McFadden, J., Njuki, E., & Griffin, T. (2023). Precision agriculture in the digital era: recent adoption on US farms. umn.edu

Bazargani, K. & Deemyad, T. (2024). Automation's impact on agriculture: opportunities, challenges, and economic effects. Robotics. mdpi.com

Gil, G., Casagrande, D. E., Cortés, L. P., & Verschae, R. (2023). Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. Smart Agricultural Technology, 3, 100069. sciencedirect.com

Aiello, G., Catania, P., Vallone, M., & Venticinque, M. (2022). Worker safety in agriculture 4.0: A new approach for mapping operator's vibration risk through Machine Learning activity recognition. Computers and Electronics in Agriculture, 193, 106637. [HTML]

Mahmud, M. S. A., Abidin, M. S. Z., Emmanuel, A. A., & Hasan, H. S. (2020). Robotics and automation in agriculture: present and future applications. Applications of Modelling and Simulation, 4, 130-140. arqiipubl.com

Kim, W. S., Lee, W. S., & Kim, Y. J. (2020). A review of the applications of the internet of things (IoT) for agricultural automation. Journal of Biosystems Engineering. researchgate.net

Hansen, B. G., Bugge, C. T., & Skibrek, P. K. (2020). Automatic milking systems and farmer wellbeing–exploring the effects of automation and digitalisation in dairy farming. Journal of Rural Studies. [HTML]

Hemathilake, D. & Gunathilake, D. (2022). Agricultural productivity and food supply to meet increased demands. Future foods. sciencedirect.com

Baur, P. & Iles, A. (2023). Replacing humans with machines: A historical look at technology politics in California agriculture. Agriculture and Human Values. [HTML]

Raj, E. F. I., Appadurai, M., & Athiappan, K. (2022). Precision farming in modern agriculture. In Smart agriculture automation using advanced technologies: Data analytics and machine learning, cloud architecture, automation and IoT (pp. 61-87). Singapore: Springer Singapore. researchgate.net

Khanna, M., Atallah, S. S., Kar, S., Sharma, B., Wu, L., Yu, C., ... & Guan, K. (2022). Digital transformation for a sustainable agriculture in the United States: Opportunities and challenges. Agricultural Economics, 53(6), 924-937. google.com

Balafoutis, A. T., Evert, F. K. V., & Fountas, S. (2020). Smart farming technology trends: economic and environmental effects, labor impact, and adoption readiness. Agronomy. mdpi.com

Bolfe, É. L., Jorge, L. A. D. C., Sanches, I. D. A., Luchiari Júnior, A., da Costa, C. C., Victoria, D. D. C., ... & Ramirez, A. R. (2020). Precision and digital agriculture: Adoption of technologies and perception of Brazilian farmers. Agriculture, 10(12), 653. mdpi.com

Bhattarai, M., Singh, G., Takeshima, H., & Shekhawat, R. S. (2020). Farm machinery use and the agricultural machinery industries in India: Status, evolution, implications, and lessons learned. An evolving paradigm of agricultural mechanisation development: How much can Africa learn from Asia, 3, 97-138. google.com

Caicedo Solano, N. E., García Llinás, G. A., & Montoya-Torres, J. R. (2020). Towards the integration of lean principles and optimisation for agricultural production systems: a conceptual review proposition. Journal of the Science of Food and Agriculture, 100(2), 453-464. researchgate.net

Hrustek, L. (2020). Sustainability driven by agriculture through digital transformation. Sustainability. mdpi.com

Jew, E. K., Whitfield, S., Dougill, A. J., Mkwambisi, D. D., & Steward, P. (2020). Farming systems and conservation agriculture: Technology, structures and agency in Malawi. Land Use Policy, 95, 104612. sciencedirect.com

Sott, M. K., Furstenau, L. B., Kipper, L. M., Giraldo, F. D., Lopez-Robles, J. R., Cobo, M. J., ... & Imran, M. A. (2020). Precision techniques and agriculture 4.0 technologies to promote sustainability in the coffee sector: state of the art, challenges and future trends. IEEE Access, 8, 149854-149867. ieee.org

Kaiser, C., Stocker, A., Viscusi, G., Fellmann, M., & Richter, A. (2021). Conceptualising value creation in data-driven services: The case of vehicle data. International Journal of Information Management, 59, 102335. sciencedirect.com

Wu, C., Wu, P., Wang, J., Jiang, R., Chen, M., & Wang, X. (2021). Critical review of data-driven decision-making in bridge operation and maintenance. Structure and infrastructure engineering, 18(1), 47-70. [HTML]

Chen, H., Jiang, B., Ding, S. X., & Huang, B. (2020). Data-driven fault diagnosis for traction systems in high-speed trains: A survey, challenges, and perspectives. IEEE Transactions on Intelligent Transportation Systems, 23(3), 1700-1716. archive.org

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for industry 4.0 maintenance applications. Electronics. mdpi.com

Rondelli, V., Franceschetti, B., & Mengoli, D. (2022). A review of current and historical research contributions to developing ground autonomous vehicles for agriculture. Sustainability. mdpi.com

Ghobadpour, A., Monsalve, G., Cardenas, A., & Mousazadeh, H. (2022). Off-road electric vehicles and autonomous robots in agricultural sector: trends, challenges, and opportunities. Vehicles, 4(3), 843-864. mdpi.com

Lenain, R., Peyrache, J., Savary, A., & Séverac, G. (2021). Agricultural robotics: part of the new deal?: FIRA 2020 conclusions. oapen.org

Lagnelöv, O., Dhillon, S., Larsson, G., Nilsson, D., Larsolle, A., & Hansson, P. A. (2021). Cost analysis of autonomous battery electric field tractors in agriculture. biosystems engineering, 204, 358-376. sciencedirect.com

Monteiro, A., Santos, S., & Gonçalves, P. (2021). Precision agriculture for crop and livestock farming—Brief review. Animals. mdpi.com

Nowak, B. (2021). Precision agriculture: Where do we stand? A review of the adoption of precision agriculture technologies on field crops farms in developed countries. Agricultural Research. [HTML]

Yang, C. (2020). Remote sensing and precision agriculture technologies for crop disease detection and management with a practical application example. Engineering. sciencedirect.com

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. Remote sensing. mdpi.com

Avizheh, M., Dadpasand, M., Dehnavi, E., & Keshavarzi, H. (2023). Application of machine-learning algorithms to predict calving difficulty in Holstein dairy cattle. Animal Production Science, 63(11), 1095-1104. publish.csiro.au

Vázquez-Diosdado, J. A., Gruhier, J., Miguel-Pacheco, G. G., Green, M., Dottorini, T., & Kaler, J. (2023). Accurate prediction of calving in dairy cows by applying feature engineering and machine learning. Preventive Veterinary Medicine, 219, 106007. [HTML]

Keceli, A. S., Catal, C., Kaya, A., & Tekinerdogan, B. (2020). Development of a recurrent neural networks-based calving prediction model using activity and behavioral data. Computers and Electronics in Agriculture, 170, 105285. wur.nl

Subeesh, A. & Mehta, C. R. (2021). Automation and digitisation of agriculture using artificial intelligence and internet of things. Artificial Intelligence in Agriculture. sciencedirect.com

Adetunji, C. O., Olaniyan, O. T., Anani, O. A., Inobeme, A., Osemwegie, O. O., Hefft, D., & Akinbo, O. (2023). Artificial Intelligence and Automation for Precision Pest Management. In Sensing and Artificial Intelligence Solutions for Food Manufacturing (pp. 49-70). CRC Press. [HTML]

Bhat, S. A. & Huang, N. F. (2021). Big data and ai revolution in precision agriculture: Survey and challenges. Ieee Access. ieee.org

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. Advanced Agrochem. sciencedirect.com

Kendall, H., Clark, B., Li, W., Jin, S., Jones, G. D., Chen, J., ... & Frewer, L. J. (2022). Precision agriculture technology adoption: a qualitative study of small-scale commercial "family farms" located in the North China Plain. Precision Agriculture, 1-33. springer.com

Kong, R., Castella, J. C., Suos, V., Leng, V., Pat, S., Diepart, J. C., ... & Tivet, F. (2021). Investigating farmers' decision-making in adoption of conservation agriculture in the Northwestern uplands of Cambodia. Land Use Policy, 105, 105404. sciencedirect.com

Ochieng, J., Afari-Sefa, V., Muthoni, F., Kansiime, M., Hoeschle-Zeledon, I., Bekunda, M., & Thomas, D. (2022). Adoption of sustainable agricultural technologies for vegetable production in rural Tanzania: Trade-offs, complementarities and diffusion. International Journal of Agricultural Sustainability, 20(4), 478-496. [HTML]

Thompson, N. M., Reeling, C. J., Fleckenstein, M. R., Prokopy, L. S., & Armstrong, S. D. (2021). Examining intensity of conservation practice adoption: Evidence from cover crop use on US Midwest farms. Food Policy, 101, 102054. sciencedirect.com