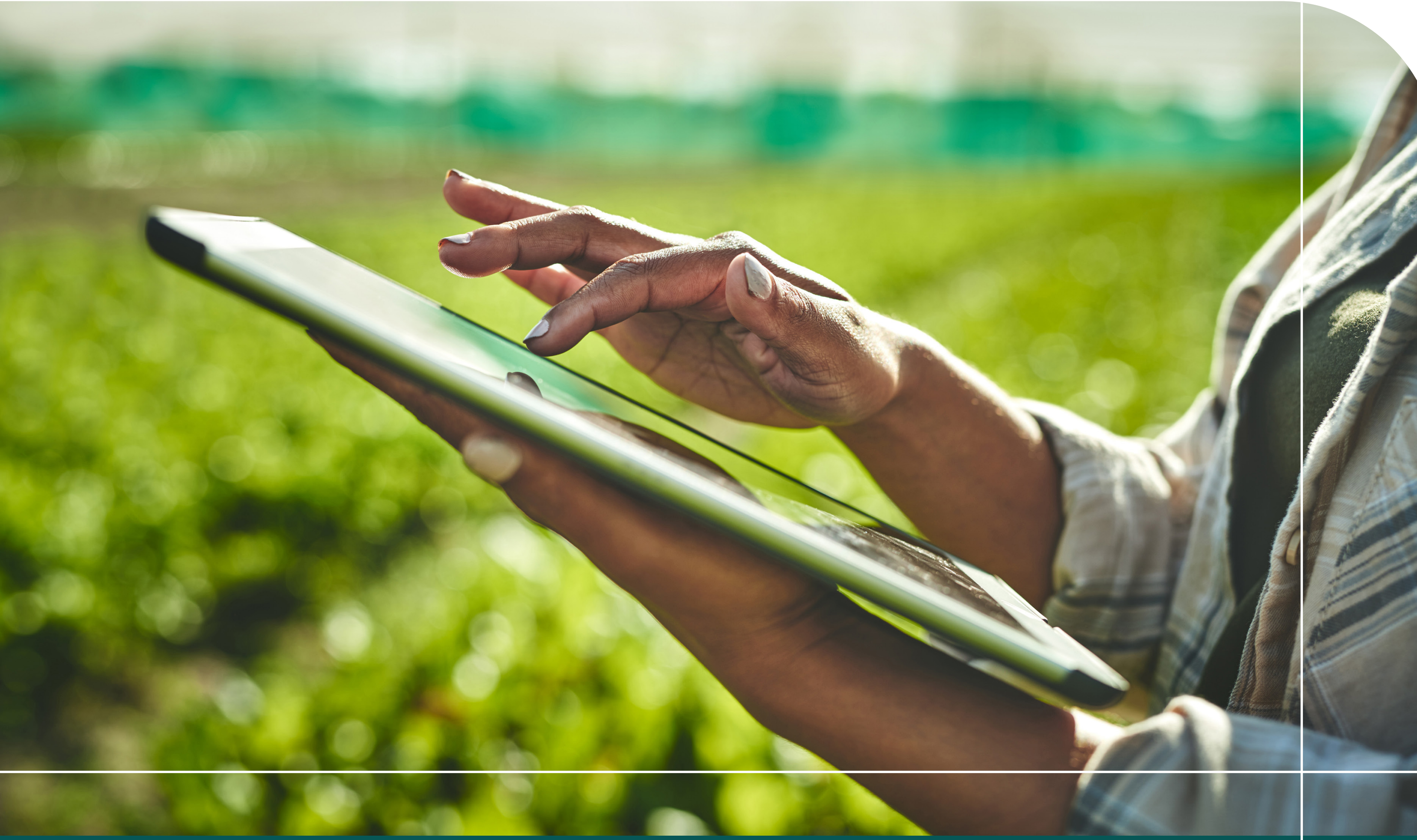
The Council for Agricultural Science and Technology



March 2025

AI in Agriculture: Opportunities, Challenges, and Recommendations

AI in Agriculture: Opportunities, Challenges, and Recommendations

AUTHORS: J. A. THOMASSON, Y. AMPATZIDIS, M. BHANDARI, R.A. FERREYRA, T. GENTIMIS, E. MCREYNOLDS, S. C. MURRAY, M. B. PETERSON, C.M. RODRIGUEZ LOPEZ, R. L. STRONG, L. O. TEDESCHI, J. VITALE, AND X. YE

I. Introduction to AI in Agriculture

Artificial intelligence (AI) is the most discussed technology of the current age and is rapidly being integrated into people's lives, reshaping industries and enabling previously unimagined innovation across the globe (Wolfert et al., 2017). AI has the potential to revolutionize agriculture by enabling advancements in precision farming, autonomous machines, and decision-support tools (Banhazi et al., 2012; Bissadu et al., 2024; and Tedeschi et al., 2021; Vinuesa et al., 2020).

AI refers to the simulation of human intelligence by computing machines, enabling them to perform tasks like problem-solving, decision-making, and learning (NASA, 2024). Machine learning (ML) is a subset of AI focused on algorithms and statistical models that improve the performance of computers on specific tasks (i.e., learn them) through experience and data. Deep learning (DL) is a subset of ML involving highly complex, multi-layer (i.e., deep) algorithms that usually operate on very large datasets for highly specific analysis and prediction. While AI and ML have been around for several decades, DL is a more recent phenomenon that emerged over roughly the last 20 years with the rapid development of semiconductors—specifically, graphical processing units (GPUs)—which has enabled fast, complex computations with massive amounts of data. An agricultural example of these technologies is the use of DL to analyze thousands of digital pictures of weeds to enable rapid detection, identification, and real-time spot spraying of individual weeds (Hu et al., 2022).

AI is rapidly getting faster, more accurate, and much further integrated into essentially all electronic systems with every passing year. Some recent advances in AI are given in Table 1 (Gao et al., 2024; Li et al., 2024; and Maslej et al., 2024), and we will use the acronyms defined there throughout this paper. As AI has been undergoing rapid expansion, agriculture has lagged behind other industries in its adoption (Abbasi et al., 2022) due in large part to unique challenges faced by farmers and the agricultural sector at large. For example, the U.S. agriculture and manufacturing industries are of similar size, but the market value of AI is roughly five times larger in manufacturing (Federal Reserve Bank of St. Louis, 2024; Precedence Research, 2024; and Research and Markets, 2024). Farmers have multiple concerns about adopting new technologies as has been seen with their cautiousness toward precision-agriculture technologies (Schimmelpfennig, 2016; and Nowak et al., 2021). Farmers look for clear opportunities for return on investment and worry about (e.g.) how a technology might change various aspects of their farm operation or jeopardize the privacy of their data. It must be considered, however, that AI differs from traditional technological tools; it is not generally bound in a physical device to purchase but is a capability integrated into existing information systems, equipment, and even the development of the genetics of seeds. In fact, many farmers are likely unaware that AI is used in many products they currently buy.

American farmers produce a great deal of the world's food. As global population continues to grow—the expected peak is currently 10.4 billion around the year 2085 (United Nations, 2025)—AI will be essential to addressing the global food security challenge, which involves producing more food with less labor on less land under unpredictable weather, etc. In this paper we explore several major aspects of the intersection of AI and agriculture at this critical point in history, including how agriculture differs from other industries in this regard. The discussion focuses on key opportunities and challenges associated with AI in agriculture, with the aim of informing policymakers, regulators, practitioners, and the public.

Table 1. Some recent advances in AI.

AI Advance	Description
Generative AI (GAI)	Can generate complex content such as text and pictures based on its consideration of a vast amount of data.
Large language models (LLMs)	A subset of GAI, usually based on the transformer architecture (see below), focusing primarily on generating human-language text.
Discriminative AI (DAI)	Models that classify data by learning boundaries between categories instead of generating new data. Different from GAI and excellent at image classification, etc. Includes most traditional ML and DL models.
Foundation models (FMs)	ML models (usually GAI) trained on a large amount of general data that can be used to create specialized AI applications like weather prediction.
Multimodal AI	Models (usually GAI) flexible enough to handle data in the forms of text, images, audio, and other data modalities.
Transformer neural-network architecture	Uses a so-called "attention mechanism" in its calculations, allowing the AI to focus on the most important data variables so it can efficiently provide accurate results, such as in prediction of crop yield.
Transfer learning (TL)	An ML technique in which a model trained on one task is reused as a starting point to learn a related but different task, transferring the knowledge gained from one domain to improve performance in another
Retrieval augmented generation (RAG)	An AI framework combining information retrieval with LLMs to help them produce relevant and accurate responses.
Digital twins	Virtual representations of physical things (e.g., a farm field) that use real-time data from sensors and AI to simulate physical behavior for prediction, etc.

II. AI Use and Development in Agriculture

General (or "strong") AI refers to a computing machine with the capability to perform new intellectual tasks across multiple knowledge domains (e.g., history and mathematics) using previous learnings in different contexts without human involvement in model training. Narrow (or "weak") AI, on the other hand, is designed to tackle better defined, more localized problems, and it requires human involvement in model training. Technically speaking, the AI we have today all falls under the narrow AI category, although GAI has vastly expanded the capabilities of the AI we have available (Neethirajan and Kemp, 2021).

A. Generative AI in agriculture

GAI refers to a system focused on human-like creation of content, such as text and pictures, based on the system's analysis of vast quantities of data. There are many types of GAI models, but ChatGPT, which debuted publicly in 2022, is the best-known GAI. It was the culmination of a massive corporate research effort that occurred at a time when the amount of information available online was increasing to unfathomable levels. Private companies have invested their resources into developing GAI because they see business opportunities, but a lucrative market to develop a GAI specifically for agriculture has not yet materialized. Furthermore, tools like ChatGPT were developed for general purposes for which tremendous amounts of data are available, but as only about 1% of U.S. citizens are engaged in farming (USDA-NASS, 2022), agricultural knowledge in the public domain is generally less than that of other sectors. AI solutions tailored to agriculture have thus lagged until recently. New approaches like TL and RAG have been developed to exploit important components of GAI, such as understanding human language, which has been used to train agriculturally focused GAI. To date, two successful case studies of GAI for agriculture have been reported: Microsoft's effort (Silva et al. 2023; Balaguer et al. 2024) and the public sector's ExtensionBot.

ExtensionBot is a GAI platform designed to enhance the work of agricultural extension services by providing farmers with science-based, accurate, and context-specific recommendations. A common question that might be asked to ExtensionBot is, how many cows can I support on my land? (Pengaard-Wilson and Vitale, 2024). Unlike general-purpose LLMs like ChatGPT, ExtensionBot is built on a smaller, curated dataset of over 360,000 extension publications, tailored to reliably address common agricultural queries. Its NLP interface facilitates user-friendly interactions, mimicking conversations between producers and extension agents. Research has shown that ExtensionBot delivers more accurate and consistent responses to agricultural questions than broader GAI models (Pengaard-Wilson and Vitale, 2024), making more focused GAI models for agriculture critical tools in an era when precision, context specificity, and reliability are essential for agriculture's digital transformation. GAI platforms commonly struggle with inconsistencies and so-called "hallucinations" (i.e., generating false or misleading results), but ExtensionBot's focused design enables it to offer recommendations aligned with local conditions and practices. Future developments could expand the capabilities of such GAI models to integrate real-time data from IoT devices, drones, and satellites, enabling precise, actionable insights for pest management, variable rate applications, weather-response strategies, and many other uses. These advancements showcase how GAI can bridge the gap between the growing magnitude of agricultural knowledge and its practical application on farms.

B. Other applications of AI in agriculture

In addition to providing contextual answers to questions, AI has been used to analyze numerical data to make predictions and provide support for management decisions. One example involves livestock monitoring systems, in which AI has been used to analyze continuously collected data in real-time and provide farmers with predictive models and decision-support that facilitates proactive management (Ellis et al., 2020). A promising application is hybrid intelligent mechanistic models (HIMMs), which combine traditional modeling approaches with ML and integrate real-time data on animal behavior (John et al., 2016), health, and environmental conditions (Halachmi et al., 2019; and Tedeschi, 2019, 2022). HIMMs and similar AI models can support decisions to improve production while minimizing environmental impact by improving feed efficiency and nutrient utilization and reducing waste and pollution.

In high-value agriculture like wine production, the location of production (e.g., Paso Robles, CA) often drives consumer preference. Unfortunately, this has led to fraud (Holmberg, 2010), with counterfeits making up large percentages of premium wines sold in certain markets (Lecat et al., 2017). AI approaches to identify counterfeit wines (Popovic et al., 2021) have been developed, leading to models focused on regional microbial biodiversity. AI has been instrumental in uncovering associations between microbial diversity and vineyard growing conditions (Coller et al., 2019), even at multiple scales including continents, countries, and regions within a country (Anand et al., 2024; Gobbi et al., 2022). Anand et al. (2024) demonstrated that DL methods can identify the variety of grapes and even the rootstock/scion combination based solely on vineyard soil microbiota. This approach holds promise for identifying genes that regulate host/microbe interactions, making it valuable not only for traceability in the wine industry but also for breeding programs focused on resilient crops (Corbin et al., 2020).

Furthermore, the recent reduction in the cost of genetic sequencing has enabled scientists to generate a wealth of data, facilitating large-scale "multi-omic" (genomic, transcriptomic, epigenomic, microbiomic, etc.) studies to identify predictive biomarkers for normal and pathological processes (Naylor, 2003) in animals and crops. The volume and dimensionality of the data pose hurdles for traditional statistical analysis methods, and computational costs can be prohibitive. On the other hand, AI tools like supervised ML, a method in which algorithms learn from data samples labeled by humans, have been used successfully to analyze “omic” data, in which models serve as prognostic or diagnostic tools (Levenson, 2010). Supervised ML has proven to be accurate at estimating animal developmental processes and diseases including biological age (Caulton et al., 2021), gestational age (Haftorn et al., 2021), and pregnancy complications (Ladd-Acosta et al., 2023). These models, combined with affordable and portable next-generation sequencers and computational methods like in-silico adaptive sampling (Martin et al., 2022), can lead to cost-effective, on-farm diagnostic kits, reducing outdated and potentially harmful preventive measures like regular use of prophylactic antibiotics. In another example, researchers recently developed an FM trained on genetic sequences of over 100,000 species (Buntz, 2025). This AI model can identify patterns in genomes and predict mutations that influence disease and protein function.

If crop yields could be predicted early in the season, farmers could make better in-season decisions about crop management and marketing, and crop breeders could make earlier decisions about which plant varieties to select for further development. Shrestha (2024) used a customized AI algorithm to predict cotton yield based on multispectral images collected with unmanned aerial vehicles (drones) multiple times early in the growing season. He incorporated feature engineering—the process of carefully preparing raw data for efficient use in ML models—and then fed the data into the customized model. He then compared the results of the customized AI model to the results of two more common AI models: Long Short-Term Memory (LSTM) and Transformer. The customized AI model successfully predicted crop yield at the end of the season based on early season data, but the Transformer model, with its attention mechanism architecture, generally outperformed the customized model and LSTM, suggesting that relatively standardized AI architectures like Transformer work well in various agricultural applications.

Like yield prediction, field-scale weather forecasting could be invaluable to farmers, enabling them to make optimal decisions on planting, irrigation, harvesting, marketing, and other critical choices. Recent AI approaches have performed well on specific high-resolution weather-prediction tasks, such as identifying drought conditions and predicting major precipitation events (Mukkavilli et al., 2023). These approaches included physics-informed FMs based on Transformer architecture, pre-trained for language modeling and vision, as well as feature engineering and fine-tuning. These FMs often can perform better than their input data and physics-based models would suggest. The models are said to be oblivious to underlying constraints, so they can disregard the constraints in an attempt to optimize and can even correct underlying model biases. Such AI methodologies are maturing to the point of facilitating the development of digital twins for global-scale weather modeling and forecasting.

Aside from using AI to generate content (GAI) and analyze numerical data for predictions and decision-support, a common use has involved discriminative AI (DAI) for image analysis in applications like insect identification (Xu et al., 2023), disease identification (Garg et al., 2024), and fruit quality classification (Lu and Lu, 2018). Many ML algorithms (Random Forest, Support Vector Machine, etc.) have been used for detection and classification of objects and conditions in images, but more recently, DL algorithms (Convolutional Neural Networks, Recurrent Neural Networks, etc.) have become commonly used. Furthermore, pre-trained DL algorithms (AlexNet, ResNet, YOLO, etc.) have been used when data are limited, because they do not require large amounts of new data to train the model (Konara et al., 2023). Finally, these DL algorithms are now often used by researchers for real-time, in-the-field image analysis, in which the desire is to detect and act quickly for agricultural tasks involving autonomous machines. Such machines must have human-like perception and decision-making skills while moving through or over an agricultural field for (e.g.) harvesting (Gharakhani et al., 2024), object identification (Yadav et al., 2023), and targeted weed-spraying (Hu et al., 2022; Taseer and Han, 2024; and Yadav et al., 2024), a capability that has been on the market since 2021 (Deere & Company, 2022).

The full potential of AI in agriculture remains untapped, but successful examples of AI-based technologies are on the market or approaching that status (Table 2). Advances in AI algorithms, along with the collection of larger and better datasets and improvements in data integration, are paving the way for additional practical uses of AI in agriculture. As AI-based technologies and datasets evolve, they will play an important role in addressing some of the most pressing challenges in food, feed, and fuel production.

Table 2. A few examples of successful AI use in agriculture. Each example is either publicly available or approaching that status.

Application	AI Method	System and Function
ExtensionBot (Oklahoma State University)	Generative AI (GAI)	Currently available natural language-based system that provides accurate and consistent responses to agricultural questions; supports extension agents in answering farmers’ questions.
FRAIL-Bot for Strawberry Harvesting (University of California-Davis)	Various AI methods	Research prototype cooperative robot for assisting human strawberry pickers; predicts when the picker will finish filling a tray and transports the tray to a collection station.
See and Spray Technology (John Deere)	Discriminative AI (DAI)	Publicly available tractor-based system for highly precise image-based detection, identification, and spot-spraying of individual weeds across a wide spray tractor at high operational speeds; enables major reductions in herbicide applications.

III. Challenges to Developing AI for Agriculture and Efforts to Mitigate Them

AI requires large volumes of data to generate insights. A key aspect of making agricultural data available for AI is to ensure that all data is generated and stored according to FAIR (findable, accessible, interoperable, and reusable) data standards. However, White et al. (2021) described numerous obstacles to applying "big data" in agriculture (Table 3). Several of those obstacles are considered below in the discussion of challenges to developing AI for agriculture. Some of the challenges are rather unique to the agricultural industry, and some are technical issues, while others are socioeconomic and/or ethical. Addressing these challenges will be critical to unlocking the full potential of AI in agriculture and ensuring its widespread and responsible adoption.

Table 3. Obstacles to applying "big data" in agriculture (White et al., 2021).

Obstacles to Applying Big Data in Agriculture
Sensor and recording errors in the data.
Inaccessibility of the data due to poor communications infrastructure.
Unusability of the data because of differences in units, format, metadata, etc.
Incompatibility of the data due to differences in recording systems, collection frequencies, etc.
Inconvenience of accessing the data due to lack of automatic data capture, data cleaning, etc.
Lack of return on investment (ROI) for data-generation costs.
Unclear "ownership" of the data and associated concerns about data privacy and compensation to farmers for use of their data.

A. Challenges unique to agriculture

Data incompatibility. Many industries outside of agriculture have made major strides in data interoperability, leading to rapid adoption of AI. However, practices on farms and in the agricultural supply chain vary widely, so agricultural data are commonly fragmented, distributed, heterogeneous, and incompatible, making it challenging to structure data such that it can be readily analyzed with AI. Efforts to standardize data formats and improve interoperability for AI systems are essential, but this requires coordination among various stakeholders and alignment across the agricultural industry. AgGateway, a non-profit organization focused on data standards to enable the agricultural industry to rapidly access information, is an example of a major effort in this regard. AgGateway's work involves on-farm and supply-chain data that can support decision making in farm operations, inventory management, and product traceability. As an example of their success, two agricultural service providers recently worked with AgGateway to streamline their data workflow in transactions like fertilizer sales, essentially enabling communication between the companies' farm management information systems (FMIS). The companies needed a common format and used AgGateway's Agricultural Data Application Programming Toolkit (ADAPT) to enable their systems to communicate. The result of the collaboration reduced order processing time and ensured that correct farm fields are selected and accurate fertilizer rates are applied (AgGateway, 2019). This type of standardization is essential to the advancement of AI in agriculture.

Lack of AI model applicability. Not only do agricultural practices vary, but crops, soil types, topography, weather, etc. also vary widely across regions and even from farm to farm. This variation makes it difficult for current AI models trained on data from one or a few specific locations to perform well in other locations (Shrestha, 2024). In general, it is important to ensure that AI models are adaptable to the diverse conditions found across regions. The development of large comprehensive datasets is key for broadly applicable AI models, and efforts are beginning to make these types of data available. For example, PlantVillage has made tens of thousands of carefully curated images of crop-plant leaves publicly available through its online platform. Remote users have used images from PlantVillage (and other large datasets) to develop AI solutions for various problems, such as broad identification of plant diseases (Isinkaye et al., 2025).

Lack of connectivity. Farmers in remote and lower-income areas, particularly those with small farms, often lack access to the infrastructure required for wireless broadband connectivity. Thus, they cannot access large datasets and cloud-based AI applications in many situations. Both the previous Presidential administrations have ordered the executive branch to accelerate the deployment and adoption of affordable, reliable, modern high-speed broadband connectivity in rural America (Trump, 2018; and USDA, 2024). Moreover, the Federal Communications Commission (2023) established a Task Force for Reviewing the Connectivity and Technology Needs of Precision Agriculture in the United States. The Task Force operated working groups on Mapping and Analyzing Connectivity on Agricultural Lands, Examining Current and Future Connectivity Demand for Precision Agriculture, Encouraging Adoption of Precision Agriculture and Availability of High-Quality Jobs on Connected Farms, and Accelerating Broadband Deployment on Unserved Agricultural Lands. A key focus of these efforts has been the ability of farms to collect, analyze, receive, and transmit large datasets, as well as to access AI-based tools. One of the difficulties is that fiber and cellular infrastructure are too expensive to build universally. Telematics systems of major agricultural equipment manufacturers often take advantage of cellular service when and where it is available. However, the advent of satellite-based wireless broadband communications, even though currently more expensive, has led the manufacturers to consider taking advantage of those satellite services (Deere & Company, 2024) where cellular services are unavailable.

Data-privacy concerns. Through technological advances in agriculture, farmers are generating more and more data. An example of an effort focused on compiling farm data from many farms is the Agricultural Data Coalition (Ag Data Coalition, 2025), which provides data for the overall food production industry and enables farmers to store all their data in a secure location, independent of any corporate data provider. The effort provides universities and other institutions a collaborative platform for agricultural research among scientists and farmers. Nevertheless, farmers may have general concerns that their data could be exploited by competitors, corporations, insurers, or even government entities. In many cases, farmers may consent to sharing their data with outside parties without fully understanding what they have consented to or its long-term implications. The common end user license agreement (EULA) is typically long and complicated, and often goes unread. Efforts are under way to clarify and resolve these issues in the agricultural industry. American Farm Bureau Federation published a set of Ag Data Core Principles about a decade ago, and the Ag Data Transparent (ADT) organization took on updating the principles as the agricultural data market changes (Janzen, 2024). The current core principles assume that farmers own information originating from their operations. A few key additional principles, most of which place the burden of data stewardship on technology providers, are paraphrased in Table 4. The challenge of data privacy intensifies with the increasing use of IoT (the "Internet of Things") devices, which collect data and are connected to the internet and thus potentially accessible by others. Agricultural examples of IoT sensors include soil sensors that continuously collect real-time, site-specific data that can (e.g.) enable AI systems to provide optimal control of agricultural practices like automated irrigation. The continuous data stream can open the door to the tracking of farm activities without consent; e.g., monitoring systems could inadvertently expose detailed patterns of land usage and farming practices. Issues of cybersecurity are a major data-privacy concern of industries worldwide, and agriculture is no different. Activities related to cybersecurity are discussed in some detail below.

Table 4. Some key Ag Data Core Principles (paraphrased from Janzen, 2024).

Providers should strive to draft simple, easy-to-understand contracts.
Providers should define the categories of data they may collect (e.g., agronomic, land, financial, machine) and be required to have the explicit consent of the farmer to collect it.
Providers shall inform farmers of the purposes of their data collection.
Farmers should be able to retrieve their data for their own use or use in other platforms.
Providers should not use farmers' data for anti-competitive activities like commodity-market speculation.
Providers should make clear whether a farmer's data is to be included in anonymized and aggregated datasets.
Providers should protect farmer data with reasonable safeguards against risks such as loss, unauthorized access, modification, or disclosure.

Resistance to change. Farmers' resistance to change has historically been a hurdle to adoption of new agricultural technologies. Many farmers have concerns about the reliability of or difficulty in using new technologies, or they fear the disruption of established farming practices. Pilot projects, demonstration sites, and real-world case studies that showcase the practical benefits of various technologies have proven to alleviate skepticism. Engaging farmers in the development and testing of AI solutions can ensure that these tools are practical and culturally appropriate (Mallinger and Baeza-Yates, 2023). An example of engaging farmers with such new technologies is the eFields program (Douridas et al., 2019), created at Ohio State University in 2017. This program has involved building a community of extension professionals, researchers, farmers, and other agriculture professionals focused on applied research and knowledge sharing. The program has had excellent success in improving technology adoption and has demonstrated the benefits of on-farm research. Aside from general farmer skepticism, people often lack trust in AI because of the "black box" nature of many AI models, which make predictions or estimations without clear explanations of the reasoning that produced them (Tedeschi, 2019 and 2023), hindering the adoption of AI solutions. Efforts toward designing trustworthy AI (TAI) systems—those that are explainable, fair, interpretable, robust, transparent, safe, and secure—are expanding and will facilitate AI adoption (Mallinger and Baeza-Yates, 2023). Furthermore, explainable AI (XAI)—a trend in AI system development—in particular helps users understand which variables and interactions are important for prediction and how they relate to response variables (Ryo, 2022).

Lack of an AI-skilled workforce. A major concern about the adoption of AI in agriculture is that farmers and agricultural workers may lack the technical proficiency needed to utilize AI tools effectively. Thus, workforce training is a crucial barrier to AI implementation (Morota et al., 2018). The FCC's Precision Agriculture Task Force recently recognized the importance of this fact, stating, "The greater incorporation of technology in agricultural production, whether to support traceability or more efficient production and farming, will demand a skilled workforce that masters both farming and technology. Dedicated investments for agriculture tech workforce development will require focused attention to technology, culture, and infrastructure in ag-based communities. These investments, however, will support the ongoing revitalization of rural communities by growing high-quality talent that can drive economic growth in the areas of the country that are often among those in most need. These strategies will keep the next generation farming and ensure an ag tech future that is attractive, profitable, and a beneficial career path" (Federal Communications Commission, 2023).

High adoption costs. Industries like healthcare and manufacturing often benefit from economies of scale and more robust infrastructure, but rural agricultural areas have less internet connectivity, computing power, and advanced technologies in general, so a significant barrier to AI adoption in agriculture is the high cost of implementing the needed technologies. The initial investment required for AI tools, ranging from broadband wireless communications to computing hardware and software to training, can be prohibitive, particularly for smaller farmers. Over the last few years large investments have gone into development and adoption of agricultural technology, including numerous AI-based technologies (Inácio Patrício and Rieder, 2018; and Talaviya et al., 2020). These investments have included billions of dollars in private venture capital and numerous grants from state and federal agencies. Federal funding sources have included the U.S. Department of Agriculture (USDA), National Science Foundation (NSF), and Small Business Administration (SBA), which have provided complementary funds to aid the private investments. The grants have different rationales and mechanisms, such as innovation grants that provide funding for agricultural-technology startups, economic development grants that provide support for regional improvements to bring about economic impact, and tax credit grants in which farmers receive subsidized purchases or tax credits after investing in new types of equipment or farming practices (Duflock, 2023).

B. Concern about the loss of agricultural knowledge in the age of AI

AI clearly can enhance productivity and also reduce the farmer's role in decision-making by shifting responsibility to automated systems. As AI becomes increasingly integrated into agriculture, farmers and farm workers could lose touch with traditional skills and knowledge essential for crop and animal management. This concern is heightened when one considers the possibility of a disruptive cybersecurity event. According to Sparrow (2021), over-reliance on AI for decision-making can diminish a farmer's ability to interpret subtle environmental cues, such as variations in soil texture, weather patterns, or pest activity, which are often informed by years of experience and intuition. Continuous use of AI for tasks like irrigation, fertilization, and pest management may lead to a decline in hands-on skills. Farmers may forget why specific tasks are necessary (e.g., pruning trees in an orchard) or how to perform them effectively (e.g., irrigation scheduling). This erosion of knowledge can have long-term implications, not only for current farmers but also for the transfer of agricultural expertise to future generations. If farmers do not maintain a foundational understanding of why certain actions are taken, they may struggle to adapt in situations in which AI tools are unavailable or fail. To address this concern, it is essential to strike a balance between leveraging AI and preserving traditional agricultural knowledge. Examples of current efforts in this regard are the USDA grant programs on (a) Enhancing Agricultural Literacy and Workforce Training, which offers grants for training K-14 educators to promote increased knowledge of food and agricultural science to train the agricultural workforce for the future; and (b) Developing Pathways, which offers grants for experiential learning for undergraduate students to gain skills applicable to the food and agriculture fields (Bampasidou, 2024). By combining AI insights with traditional expertise, the agricultural community can create a resilient and adaptable workforce able to navigate the complexities of modern agriculture.

C. Cybersecurity

The integration of AI into agriculture, particularly in AI-based autonomous machines, introduces a host of cybersecurity vulnerabilities (Giaretta et al., 2022). As farms begin to use autonomous machinery for scouting, harvesting, spraying, etc., simple cyber failures may occur, or even worse, cyberattacks may target these systems. Threat actors could exploit vulnerabilities in the software or communication networks of these machines, causing disruptions and even malicious actions in agricultural operations (Jain & Sharma, 2021). Cyber-attacks on AI-based systems can lead to data breaches, operational disruptions, and financial losses, posing threats to farmers and stakeholders across the agricultural value chain. A critical issue is the potential for malicious actors to disable or take control of autonomous machinery, e.g., a compromised robotic sprayer might be rendered inoperable during a critical time for crop protection, leaving crops vulnerable to diseases or pests. Another example is a compromised autonomous harvester, which could delay timely harvest, leading to financial losses and reduced crop quality. These scenarios threaten the economic stability of farms and jeopardize food security on a broader scale (Dreo et al., 2021), not to mention considerations of harm to human life and property. The agricultural community is beginning to take note of this threat. For example, Iowa State University has a webpage on cybersecurity for grain farming (Stevens, 2025), and a systematic literature review on agricultural cybersecurity was recently published (Campoverde-Molina and Luján-Mora, 2024). Given the interconnectivity between the food and agriculture industry and critical infrastructure industries, securing digital agricultural systems is vital for ensuring food security, economic stability, and national resilience. By proactively addressing cybersecurity challenges, the agricultural sector can minimize the risk of cyberattacks and safeguard the benefits of AI, as well as autonomous machines and systems.

D. Needs of workers involving AI in agriculture

AI has the potential to transform the experience of the agricultural workforce by improving productivity, enhancing working conditions, and reducing the physical strain of labor. An example of this is the development of an AI-based robotic cart called FRAIL-bot, which tracks the strawberry picking process of workers so it can collect a full tray of strawberries from a worker immediately after the worker is finished filling it (Peng et al., 2022). Workers commonly must carry trays a long distance to and from the edge of the field each time they fill a tray. The FRAIL-bots can provide workers with up to 25% more picking time, which should lead to greater pay and higher yield each season. The realization of such benefits hinges on addressing the unique needs and challenges that agricultural workers face in adapting to new technologies. Workforce training, discussed previously, is a key factor in enabling the successful adoption of AI, which commonly requires workers to interact with complex interfaces and interpret data; this can be daunting without proper training. Another concern among agricultural workers is that AI and automation may lead to job displacement. However, AI should ideally be viewed as a tool to complement human workers rather than replace them, particularly in agriculture, where labor shortages tend to be the driver of automation. By helping to automate repetitive and physically demanding ("dull, dirty, dangerous, and difficult") tasks, AI can free up workers to focus on higher-value activities, such as problem-solving, decision-making, and strategic planning. This shift could improve job satisfaction and lead to a more skilled workforce earning a higher standard of living. Addressing these concerns and promoting the concept that AI enhances, rather than replaces, human labor is essential to foster trust and acceptance among workers. Furthermore, Mallinger and Baeza-Yates (2023) highlighted the importance of the participatory design approach, in which workers collaborate with developers and stakeholders to co-create AI tools that improve their daily tasks and overall work experience, empowering the workers and building trust in the technology, thus helping to ensure its widespread adoption.

E. Needs of consumers involving AI in agriculture

The integration of AI into agriculture holds promise to not only transform farming practices, but also to address broader societal needs, including concerns about production and supply-chain practices, food safety, and consumer health. Consumers today are more concerned than ever before about the quality, safety, and nutritional value of their food. Currently, IoT devices such as sensors in cold storage, coupled with AI-based analytics and traceability (Misra et al., 2022), can provide consumers with information about product origin, production practices, processing practices, and transportation. Blockchain technology is commonly used with AI to provide data integrity, minimizing the risk of error in supply-chain data and providing transparency that builds consumer trust. AI can safeguard public health by detecting food contaminants early, enabling rigorous safety standards to be maintained throughout the food supply chain (Liu et al., 2023) and reducing response times to issues requiring product recalls. This ability to monitor products through the supply chain helps ensure food safety and quality (Sahni et al., 2021) and empowers consumers to make informed choices at a time when concerns about food origin and quality are high priorities (Kudashkina et al., 2022). AI also plays a crucial role in improving the nutritional value of crops through precision breeding and optimization techniques. By using AI to enhance the nutritional profiles of crops, problems like malnutrition and diet-related chronic diseases can be minimized. Furthermore, AI can support the increasing focus on food as "precision nutrition," in which personalized diets are tailored to individual health needs. By analyzing agricultural data alongside personal health metrics, AI can help design nutrition plans for individuals with specific health conditions, such as allergies or vulnerabilities to foodborne illnesses (Feeney, 2023).

F. Ethical considerations of AI in agriculture

In addition to concerns about the cybersecurity of IoT data, the aggregation of geospatial data, sometimes gleaned from satellite images across multiple farms for large-scale analysis, adds an additional layer of risk. Such data can be pooled to improve predictions (e.g., for crop yield forecasting or disease detection) and may potentially be repurposed for commercial or regulatory purposes without the consent of farmers and potentially against their interests. Corporations might, for example, leverage this type of data to influence market prices or redistribute resources in ways that may disadvantage smaller or less technologically advanced farms. Concerns about some aspects of this issue can be assuaged by adherence to the aforementioned Ag Data Core Principles. However, in addition to these concerns, data used in agricultural AI applications are typically tied to specific locations, communities, and environmental conditions and can be used in ways that negatively reinforce the differences between large and small farms or wealthy and poor farms if not handled responsibly (Klerkx and Rose, 2020). For example, AI models trained on data from large farms in high-data, high-income regions may not perform well on small farms and in low-data, low-income regions. USDA-NIFA is currently funding exemplary research related to this issue (Mississippi State University, 2024), which considers the social and economic impacts of autonomous agricultural systems on small farms.

G. Research Funding

Many universities have made strategic investments in hiring experts specializing in AI applications for agriculture, leading to a surge in innovative research. For example, the University of Florida recently hired 100 new AI-focused faculty members, 15 of whom are focused on AI for agricultural applications (Haire, 2022). These experts bring unique expertise in areas such as precision farming (Lee et al., 2024), crop monitoring, predictive analytics, and autonomous systems, significantly advancing this field of study. However, this influx of researchers has also highlighted a critical challenge: the availability of funding for AI-based agricultural research remains low relative to the demand. Despite the strong potential for AI to revolutionize agriculture, the pool of funds for research projects dedicated to this interdisciplinary field has not expanded proportionately. Funding agencies and programs often categorize AI in agriculture under broader disciplines, such as computer science or agricultural sciences, which results in competition among researchers from diverse backgrounds. This situation is further compounded by the increasing number of institutions and researchers entering the field, all competing for the same limited funding opportunities. The limited availability of funds can have detrimental effects on the development of AI for agriculture. First, it may slow the pace of innovation as researchers spend time and effort competing for grants rather than advancing their projects. Second, it can hinder collaboration, as researchers may focus on competing for resources rather than sharing knowledge and building partnerships. Lastly, early career researchers may face disproportionate challenges in securing funding, limiting the breadth of ideas and approaches that can help drive scientific progress. Over the last few years, NSF and USDA-NIFA have collaborated to fund AI centers at various institutions, but only a handful of these focus on agriculture.

In 2021, a USDA-administered Hatch Multistate Project on this subject was formed, S1090 AI in Agroecosystems: Big

Data and Smart Technology-Driven Sustainable Production. An outgrowth of this project has been an annual AI in Agriculture conference, starting in 2022 and hosted by Auburn University. Subsequent conferences have been hosted by University of Florida in 2023 and Texas A&M University in 2024. The rollout of this CAST paper occurred at the 4th AI in Agriculture conference in 2025, hosted by Mississippi State University.

IV. Major Considerations in Developing AI for Agriculture

A. Promoting Innovation and Competition for AI in Agriculture

AI-based technologies must become a central focus in the drive for innovation in agriculture, especially as the industry faces increasing challenges related to food security, food safety, weather-event resilience, and environmental risk (Sachithra and Subhashini, 2023). Fostering AI innovation in agriculture requires three things: breaking down structural barriers in agriculture that limit AI's potential and broad adoption, collaboration across disciplines and industry sectors, and building a competitive landscape.

Agricultural-industry barriers to innovation in and adoption of AI-based technologies include limited access to technology and limited digital literacy among farmers and farm workers. Most farms are rural, and rural areas tend to lack access to data communications infrastructure. Furthermore, small-scale farms commonly lack access to advanced technologies (e.g., precision agriculture) and may not have access to training programs that larger-scale farms take advantage of. As mentioned previously, multiple presidential administrations have been working through various agencies to build out fiber and wireless infrastructure across the country, but the vastness of the country and low population in rural areas makes this difficult. Meanwhile, low-earth-orbit satellite communications have come online, and these, while typically more expensive than cellular, can fill the gaps in achieving broadband communications at the last acre. Furthermore, extension efforts are beginning to take shape (Pengaard-Wilson and Vitale, 2024) that will enable farmers to learn how to leverage AI-tools for better decision-making in areas like crop management, pest control, and resource optimization.

AI innovation and integration into agricultural applications requires collaboration across disciplines and industries (Jung et al., 2021; Subeesh and Mehta, 2021; and Strong et al., 2023). Academic institutions train the future workforce in numerous disciplines, including agriculture, engineering, computer science, etc. These disciplines conduct collaborative research on AI applications specific to agriculture, including developing models and producing evidence-based recommendations. Corporations, on the other hand, bring business acumen, technological expertise, and the ability to scale solutions. Government can support innovation, provide funding, and ensure access to AI-based technologies. When the various disciplines and sectors work together, they can create an ecosystem that fosters AI-based innovation (Bitko, 2024) while ensuring that solutions are scalable, sustainable, and widely accessible. When these things happen, farmers and society benefit.

A competitive landscape is another driving force in AI innovation, encouraging commercial participants to push the boundaries of what is possible. Creating healthy competition requires an environment where various players, from large corporations to small tech startups, can innovate freely. For the smaller innovators, access to capital, intellectual property protections, and market access can improve their ability to compete, facilitating the introduction of unconventional approaches. A promising avenue to foster competition is open-source platforms that allow for exchange of ideas, technologies, and data (Crüwell et al., 2019; Muñoz-Tamayo et al., 2022; and Janssen et al., 2017). An interesting example comes from the Meta corporation, whose decision makers made their internally developed LLM open-source in 2023. In early 2025, a small Chinese company called DeepSeek announced it had used open-source code to build a powerful AI system at much lower cost than rival systems (Metz and Isaac, 2025). Many believe that open-source technologies enable small innovators to compete with larger firms by facilitating collaboration between them and allowing the small innovators to develop AI-based solutions while benefiting from the resources and expertise of larger players. Open-source platforms can also promote transparency and inclusiveness, ensuring that innovations are accessible to a wide range of users, from tech-savvy farmers to those just beginning to explore AI. Furthermore, public and private funding initiatives can help accelerate the pace of innovation. Government grants, industry-backed research initiatives, and innovation contests can provide incentives for companies and research teams to develop AI applications that address pressing challenges facing agriculture.

B. Advancing American leadership in AI for agriculture

While the U.S. is uniquely positioned to lead globally in applying AI to agricultural challenges, two impressive major international AI efforts, the DeepSeek and Manus GAI platforms (Baptista, 2025), have been reported in the last few weeks before the publication of this paper, emphasizing the need for U.S. vigilance to maintain its leadership role. With its tremendous agricultural productivity, robust research infrastructure, rich history of agricultural innovation, and unparalleled access to world-class technological resources, the U.S. can set the benchmark for highly productive, efficient, and resilient food systems facilitated by AI (White et al., 2018). In addition to the rapid buildout of AI infrastructure—data centers, along with adequate energy to meet the demand—multidisciplinary collaboration, mentioned previously, is at the core of advancing U.S. leadership. Technological innovation in AI for agriculture is crucial, but transitioning from theoretical models to real-world applications requires the collective expertise of numerous disciplines including agronomy, engineering, computer science, etc.

The U.S. has a strong foundation for this collaborative effort, with numerous academic institutions conducting multidisciplinary research at the forefront of AI for agriculture. For example, the University of Florida's (UF) AI partnership with NVIDIA has provided the avenue and incentive for agricultural researchers to focus on AI to address pressing global challenges, including food insecurity, weather resilience, and profitable farming. Through this partnership, UF has created a powerful AI data center that allows researchers from many disciplines to leverage state-of-the-art computational resources for AI-based agricultural research.

C. Opportunities for Standards for AI in agriculture

In addition to the agricultural data standards being developed by organizations like AgGateway, standards specific to AI and its use in agriculture are important. Many types of AI applications for agriculture are being developed in parallel by numerous companies, academic institutions, and government organizations, which are racing to create innovative solutions in a highly dynamic environment. These entities are often expert in specific aspects of AI, such as model engineering or application development, yet many lack comprehensive expertise in integrating AI safely and effectively into large-scale agricultural systems. This is particularly evident when AI is incorporated into existing systems, such as farm management software. Teams with strong software development skills may not fully grasp how to address issues like bias, trustworthiness, and data quality in agricultural systems that need to meet industry standards for reliability and security.

To ensure AI systems in agriculture are safe, efficient, and reliable, the establishment of clear standards is critical. Standards are documents that define best practices, protocols, and frameworks for developing products and processes across companies and industries. In the context of AI for agriculture, standards can help guide the development of robust, trustworthy systems that can be integrated seamlessly into farm operations. These standards are typically developed by international bodies like the International Organization for Standardization (ISO), International Electrotechnical Commission (IEC), and Institute of Electrical and Electronics Engineers (IEEE), as well as national organizations such as the American National Standards Institute (ANSI) and the American Society of Agricultural and Biological Engineers (ASABE).

Although the implementation of standards is generally voluntary, unless mandated by legislation, adherence to them can provide significant benefits to developers and end-users. For developers, following established standards can ensure that AI systems are not only efficient and effective but also safe, secure, and ethical in their applications, and it can help ensure their products are marketable. For end-users, such as farmers and agribusinesses, standards offer a reliable way to assess the quality and trustworthiness of AI-based tools, enabling informed decision-making when adopting new technologies. Furthermore, certification processes (e.g., the work of the Agricultural Industry Electronics Foundation, or AEF) that verify AI products' compliance with industry standards offer an additional layer of transparency and accountability.

As AI adoption in agriculture continues to grow, a rising number of international standardization initiatives are emerging to support these efforts. These initiatives aim to address key challenges, such as system interoperability (e.g., the ability of a particular brand of tractor to communicate with another brand of hay baler), algorithmic transparency, and data privacy, which are essential for ensuring that AI systems operate safely and ethically within agricultural contexts. By developing and adhering to these standards, stakeholders can foster greater trust in AI, promote its responsible use, and ensure that it contributes to resilient agriculture and food systems. A growing number of international standards and standardization initiatives can both enable many opportunities in and address the challenges of AI in agriculture. A couple of examples are as follows:

- ISO/IEC TR 5469:2024. Artificial intelligence — Functional safety and AI systems
- 7010-2020 - IEEE Recommended Practice for Assessing the Impact of Autonomous and Intelligent Systems on Human Well-Being

V. Summary and Recommendations

AI has tremendous potential to benefit agriculture in terms of improved efficiency, precision, productivity, lifestyle improvement, etc. Efforts in and examples of GAI, as well as numerous other forms of AI for agriculture, are proliferating. On the other hand, several barriers exist to realizing the full potential of AI in agriculture (Table 5A). While the development of AI-based technologies for agriculture grows, albeit slowed by these barriers, concerns exist around societal implications of how AI will be used in agriculture (Table 5B). On the other hand, opportunities for the growth of AI in agriculture and its potential for positive effects on the industry are immeasurable. To take advantage of these opportunities, it is essential to promote innovation and competition in the industry, advance American leadership in AI's development for agriculture, and promote the development of standards that can support the growth of AI in agriculture while improving efficiency and reliability in safe and ethical ways. Along these lines, we recommend that policymakers ponder some specific initiatives, changes, and lines of thinking to promote AI in agriculture (Table 6). AI has immense potential to enable a next step change in agriculture. Expanding funding, training, etc. can enhance the adoption of AI in agriculture, supporting farm operations of various sizes and other agricultural stakeholders by helping them access advanced AI tools and the know-how to use them. Such efforts can position the United States as a global leader in agricultural AI, driving economic growth, ensuring food security, and promoting environmentally sound practices.

Table 5. A. Barriers to AI in agriculture. B. Concerns about societal implications of AI in agriculture.

A. Barriers to AI in agriculture
Incompatibility of agricultural data.
Difficulty in making AI models widely applicable for agriculture.
Lack of broadband connectivity in rural areas and farm fields.
Concerns about lack of privacy in agricultural data.

B. Concerns about societal implications of AI in agriculture
Loss of agricultural knowledge by farmers and workers using AI.
Cybersecurity issues.
Worker and consumer needs and ethical issues.
Lack of adequate research funding.

Table 6. Recommendations for policymakers to promote important aspects of AI in agriculture.

Aspect Promoting AI in Agriculture	Recommendations
Competitive environment	Facilitate a competitive environment by promoting interdisciplinary collaboration, cooperation across industry sectors, consideration of promoting open-source tools, etc.
	Foster a self-regulatory competition approach among funding bodies, industry, academics, and farmers (consider the 1975 Asilomar conference for biotechnology; Hurlbut, 2025).
	Promote alignment of AI development with real-world agronomic practice and economic and environmental goals.
	Encourage farmers to engage with AI systems and data repositories.
Broad benefit of AI in agriculture	Ensure benefit for large and small and high- and low-income farms.
	Promote decentralized data so as not to expose sensitive information.
	Promote diversified datasets so tools represent various geographies.
	Promote accessible and affordable AI-based systems for agriculture.
	Encourage offline functionality for farmers with poor internet connectivity.
Practical and transparent algorithms	Promote tailoring AI to specific needs of farmers to make it relatable and credible.
	Facilitate workers' engagement in designing and implementing tools to ensure their perspectives are considered and technologies are practical.
	Encourage TAI and XAI to encourage stakeholders to trust and understand AI-based decisions and recommendations.
Education and training	Provide agricultural and technical training, particularly in AI related skills.
	Equip extension agents and the agricultural workforce with necessary skills to operate AI-based technologies.
	Promote decision-making benefits of precision agriculture and AI-based technologies to farmers and agricultural supply chain members.
Enabling funding	Promote AI-in-agriculture research to catalyze discoveries and ensure U.S. competitiveness.
	Consider additional AI institutes focused on agriculture, as envisioned by the National Artificial Intelligence Initiative (NAII).
	Promote broadband wireless communications infrastructure to enable farmers to participate in AI-based innovations.
	Promote public-private partnerships to create a financial ecosystem for innovation.
Ag Data Core Principles	Promote simple contracts between data providers and farmers.
	Promote broad data protections for farmers.
Cybersecurity	Develop a comprehensive strategy to prevent unauthorized access, etc.
Standards	Promote standards for AI-based agricultural technologies to facilitate interoperability as well as quality and safety assurance.

Bibliography

1. Ag Data Coalition (2025). https://agdatacoalition.org/. Accessed March 2, 2025.

2. AgGateway (2019). AgGateway case studies: Central Farm Service uses ADAPT to streamline processes in agronomy and operations. https://aggateway.org/Portals/1010/WebSite/About%20Us/CASE%20STUDY%20-%20Central%20Farm%20Services.pdf?ver=2019-02-14-034653-433. Accessed March 23, 2025.

3. Abbasi, R., Martinez, P., & Ahmad, R. (2022). The digitization of agricultural industry – a systematic literature review on agriculture 4.0. Smart Agricultural Technology 2(1):100042. https://doi.org/10.1016/j.atech.2022.100042.

4. Balaguer, A., Benara, V., de Freitas Cunha, R. L., Estevão Filho, R. D. M., Hendry, T., Holstein, D., ... & Chandra, R. (2024). RAG vs fine-tuning: Pipelines, tradeoffs, and a case study on agriculture. arXiv:2401.08406v3 [cs.CL]. https://doi.org/10.48550/arXiv.2401.08406.

5. Bampasidou, M., Goldgaber, D., Gentimis, T., & Mandalika, A. (2024). Overcoming 'Digital Divides': Leveraging higher education to develop next generation digital agriculture professionals. Computers and Electronics in Agriculture 224(1):109181. https://doi.org/10.1016/j.compag.2024.109181.

6. Banhazi, T. M., Lehr, H., Black, J. L., Crabtree, H., Schofield, P., Tscharke, M., & Berckmans, D. (2012). Precision Livestock Farming: An international review of scientific and commercial aspects. International Journal of Agricultural and Biological Engineering 5 (3):1-9. https://doi.org/10.3965/j.ijabe.20120503.001.

7. Baptista, E. (2025). Beijing boosts AI startup Manus, as China looks for the next DeepSeek. https://www.reuters.com/technology/artificial-intelligence/beijing-boosts-ai-startup-manus-china-looks-next-deepseek-2025-03-21/. Accessed March 22, 2025.

8. Bissadu, K. D., Sonko, S., & Hossain, G. (2024). Society 5.0 enabled agriculture: Drivers, enabling technologies, architectures, opportunities, and challenges. Information Processing in Agriculture. https://doi.org/10.1016/j.inpa.2024.04.003.

9. Bitko, G. (2024). Sustainable AI: an innovative future needs public-private partnership. Forbes. https://www.forbes.com/sites/gordonbitko/2024/10/10/sustainable-ai-an-innovative-future-needs-public-private-partnership/. Accessed March 2, 2025.

10. Buntz, B. (2025). Evo 2 AI promises to accelerate genetic engineering and synthetic biology. R&D World, February 19, 2025. https://www.rdworldonline.com/evo-2-ai-promises-to-accelerate-genetic-engineering-and-synthetic-biology/.

11. Campoverde-Molina, M., & Luján-Mora, S. (2024). Cybersecurity in smart agriculture: A systematic literature review. Computers & Security 150(1):104284. https://doi.org/10.1016/j.cose.2024.104284.

12. Crüwell, S., v. Doorn, J., Etz, A., Makel, M. C., Moshontz, H., Niebaum, J. C., Orben, A., Parsons, S., & Schulte-Mecklenbeck, M. (2019). Seven easy steps to open science. Zeitschrift für Psychologie 227(4):237-248. https://doi.org/10.1027/2151-2604/a000387.

13. Deere & Company (2022). Deere launches See & Spray™ Ultimate: in-season targeted spray technology combined with a dual product solution system for corn, soybeans, and cotton. https://www.deere.com/en/news/all-news/see-spray-ultimate. Accessed March 23, 2025.

14. Deere & Company (2024). John Deere announces strategic partnership with SpaceX to expand rural connectivity to farmers through satellite communications. https://www.deere.com/en/our-company/static/john-deere-partnership-with-spacex. Accessed March 23, 2025.

15. Douridas, A., Bruynis, C., Hawkins, E., Badertscher, B., Barker, J., Bennett, A., ... & Zoller, C. (2019). eFields: connecting science to fields. In Proc. 22nd International Farm Management Congress. Launceston, Tasmania, Australia.

16. Dreo, G., Kotenko, I., Lechner, R., Rass, S., & Szalachowski, P. (2021). Cybersecurity and resilience in AI-based smart agriculture: Emerging threats and solutions. Journal of Cybersecurity Research 10(2):45-63. https://doi.org/10.1080/27685241.2021.2008777.

17. Duflock, W. (2023). Ag should prefer economic development grants over innovation and technology adoption grants. Medium. https://medium.com/@waltduflock/ag-should-prefer-economic-development-grants-over-innovation-and-technology-adoption-grants-64b737b2235d. Accessed February 23, 2025.

18. Ellis, J. L., Jacobs, M., Dijkstra, J., van Laar, H., Cant, J. P., Tulpan, D., & Ferguson, N. (2020). Review: Synergy between mechanistic modelling and data-driven models for modern animal production systems in the era of big data. Animal 14(S2):s223-s237. https://doi.org/10.1017/S1751731120000312.

19. Federal Communications Commission (2023). Report of the task force for reviewing the connectivity and technology needs of precision agriculture in the United States. https://www.fcc.gov/sites/default/files/2023-Report-FCC-Precision-Ag-Task-Force.pdf. Accessed February 23, 2025.

20. Federal Reserve Bank of St. Louis (2024). Contributions to percent change in real GDP by industry. https://fred.stlouisfed.org/series/CPGDPMA. Accessed March 22, 2025.

21. Feeney, I. (2023). The next generation of precision nutrition science. City Health Spring 2023. https://publications.sph.cuny.edu/city-health-2023/the-next-generation-of-precision-nutrition-science/.

22. Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., ... & Wang, H. (2024). Retrieval-augmented generation for large language models: A survey. arXiv:2312.10997v5 [cs.CL]. https://doi.org/10.48550/arXiv.2312.10997.

23. Garg, T., Dwivedi, P., Mishra, M. K., Joshi, N. C., Shrivastava, N., & Mishra, V. (2024). "Artificial intelligence in plant disease identification: Empowering agriculture." Methods in Microbiology (Vol. 55, pp. 179-193). Academic Press. https://doi.org/10.1016/bs.mim.2024.05.007.

24. Gharakhani, H., Thomasson, J. A., Lu, Y., & Reddy, K. R. (2024). Field test and evaluation of an innovative vision-guided robotic cotton harvester. Computers and Electronics in Agriculture 225(1):109314. https://doi.org/10.1016/j.compag.2024.109314.

25. Giaretta, E., Cruz, J., & Fernandes, B. (2022). Artificial intelligence in cybersecurity for smart agriculture: A comprehensive review of current trends, cyber threats, AI applications, and ethical issues. Cybersecurity AI Journal 5(1):102-130. doi.org/10.1007/s10207-022-00657-x.

26. Gobbi, A., Acedo, A., Imam, N., Santini, R. G., Ortiz-Álvarez, R., Ellegaard-Jensen, L., ... & Hansen, L. H. (2022). A global microbiome survey of vineyard soils highlights the microbial dimension of viticultural terroirs. Communications Biology 5(1):241. https://doi.org/10.1038/s42003-022-03202-5.

27. Halachmi, I., Guarino, M., Bewley, J., & Pastell M. (2019). Smart animal agriculture: Application of real-time sensors to improve animal well-being and production. Annual Review of Animal Biosciences 7(1):403-425. https://doi.org/10.1146/annurev-animal-020518-114851.

28. Haire, B. (2022). Building agriculture's AI hub. Farm Progress. https://www.farmprogress.com/technology/building-agriculture-s-ai-hub. Accessed February 25, 2025.

29. Hu, C., Xie, S., Song, D., Thomasson, J. A., Hardin IV, R. G., & Bagavathiannan, M. (2022). Algorithm and system development for robotic micro-volume herbicide spray towards precision weed management. IEEE Robotics and Automation Letters 7(4):11633-11640. https://doi.org/10.1109/LRA.2022.3191240.

30. Hurlbut, J. B. (2025). Taking responsibility: Asilomar and its legacy. Science 387(6733):468-472. https://doi.org/10.1126/science.adv3132.

31. Inácio Patrício, D., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. Computers and Electronics in Agriculture 153(1):69–81. https://doi.org/10.1016/j.compag.2018.08.001.

32. Isinkaye, F. O., Olusanya, M. O., & Akinyelu, A. A. (2025). A Multi-class hybrid variational autoencoder and vision transformer model for enhanced plant disease identification. Intelligent Systems with Applications 26(1):200490. https://doi.org/10.1016/j.iswa.2025.200490.

33. Jain, R., & Sharma, P. (2021). The role of AI in precision agriculture and associated cyber-security challenges. International Journal of Agricultural Research, Innovation and Technology 8(3):75-89. doi.org/10.1016/j.ijat.2021.05.004.

34. Janssen, S. J. C., Porter, C. H., Moore, A. D., Athanasiadis, I. N., Foster, I., Jones, J. W., & Antle, J. M. (2017). Towards a new generation of agricultural system data, models and knowledge products: Information and communication technology. Agricultural Systems 155(1):200-212. https://doi.org/10.1016/j.agsy.2016.09.017.

35. Janzen, D. (2024). New concepts in the updated core principles for ag data. https://www.aglaw.us/janzenaglaw/2024/5/16/highlights-from-the-updated-ag-data-core-principles. Accessed February 23, 2025.

36. John, A. J., Clark, C. E. Freeman, M. J. Kerrisk, K. L. Garcia, S. C., & Halachmi, I. (2016). Review: Milking robot utilization, a successful precision livestock farming evolution. Animal 10(9):1484-1492. https://doi.org/10.1017/s1751731116000495.

37. Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Current Opinion in Biotechnology 70(1):15–22. https://doi.org/10.1016/j.copbio.2020.09.003.

38. Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? Global Food Security 24(1):100347. https://doi.org/10.1016/j.gfs.2019.100347.

39. Konara, B., Krishnapillai, M., & Galagedara, L. (2024). Recent trends and advances in utilizing digital image processing for crop nitrogen management. Remote Sensing 16(23):4514. https://doi.org/10.3390/rs16234514.

40. Kudashkina, K., Corradini, M. G., Thirunathan, P., Yada, R. Y., & Fraser, E. D. (2022). Artificial Intelligence technology in food safety: A behavioral approach. Trends in Food Science & Technology 123(1):376-381. https://doi.org/10.1016/j.tifs.2022.03.021.

41. Lecat, B., Brouard, J., & Chapuis, C. (2017). Fraud and counterfeit wines in France: An overview and perspectives. British Food Journal 119(1):84-104. https://doi.org/10.1108/BFJ-09-2016-0398.

42. Lee, C. L., Strong, R., Briers, G., Murphrey, T., Rajan, N., & Rampold, S. (2024). Factors predicting innovation-decisions: The effects of performance expectancy, social influence, and facilitating conditions on U.S. Extension's promotion of precision agriculture technologies. NJAS: Impact in Agricultural and Life Sciences 96(1). https://doi.org/10.1080/27685241.2024.2420111.

43. Li, J., Xu, M., Xiang, L., Chen, D., Zhuang, W., Yin, X., & Li, Z. (2024). Foundation models in smart agriculture: Basics, opportunities, and challenges. Computers and Electronics in Agriculture 222(1):109032. https://doi.org/10.1016/j.compag.2024.109032.

44. Liu, Z., Wang, S., Zhang, Y., Feng, Y., Liu, J., & Zhu, H. (2023). Artificial intelligence in food safety: A decade review and bibliometric analysis. Foods 12(6):1242.

45. Lu, Y., & Lu, R. (2018). Detection of surface and subsurface defects of apples using structured-illumination reflectance imaging with machine learning algorithms. Trans. American Society of Agricultural and Biological Engineers 61(6):1831-1842. https://doi.org/10.13031/trans.12930.

46. Mallinger, K., & Baeza-Yates, R. (2024). Responsible AI in farming: a multi-criteria framework for sustainable technology design. Applied Sciences 14(1):437. https://doi.org/10.3390/app14010437.

47. Maslej, N. et al. (2024). Artificial intelligence index report 2024, Human-Centered Artificial Intelligence. https://coilink.org/20.500.12592/h70s46h. Accessed on February 23, 2025.

48. Metz, C., & Isaac, M. (2025). Meta engineers see vindication in DeepSeek's apparent breakthrough. https://www.nytimes.com/2025/01/29/technology/meta-deepseek-ai-open-source.html. Accessed February 28, 2025.

49. Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko A. (2022). IoT, big data, and artificial intelligence in agriculture and food industry. IEEE Internet Things Journal 9(9):6305-6324. https://doi.org/10.1109/JIOT.2020.2998584.

50. Mississippi State University (2024). Social and economic impacts of agricultural autonomy on small farms: status and recommendations. USDA National Institute for Food and Agriculture. https://portal.nifa.usda.gov/enterprise-search/ss/2241. Accessed February 25, 2025.

51. Morota, G., Ventura, R. V., Silva, F. F., Koyama, M., & Fernando, S. C. (2018). Big data analytics and precision animal agriculture symposium: Machine learning and data mining advance predictive big data analysis in precision animal agriculture. Journal of Animal Science 96(4):1540-1550. https://doi.org/10.1093/jas/sky014.

52. Mukkavilli, S. K., Civitarese, D. S., Schmude, J., Jakubik, J., Jones, A., Nguyen, N., ... & Weldemariam, K. (2023). AI foundation models for weather and climate: Applications, design, and implementation. arXiv:2309.10808v2 [cs.LG]. https://doi.org/10.48550/arXiv.2309.10808.

53. Muñoz-Tamayo, R., Nielsen, B. L., Gagaoua, M., Gondret, F., Krause, E. T., Morgavi, D. P., Olsson, I. A. S., Pastell, M., Taghipoor, M., L. Tedeschi, et al. (2022). Seven steps to enhance open science practices in animal science. PNAS Nexus 1(1):1-6. https://doi.org/10.1093/pnasnexus/pgac106.

54. NASA (2024). What is artificial intelligence? https://www.nasa.gov/what-is-artificial-intelligence. Accessed March 22, 2025.

55. Neethirajan, S., & Kemp, B. (2021). Digital livestock farming. Sensing and Bio-Sensing Research 32(1):100408. https://doi.org/10.1016/j.sbsr.2021.100408.

56. 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 https://doi.org/10.1007/s40003-021-00539-x.

57. Peng, C., Vougioukas, S., Slaughter, D., Fei, Z., & Arikapudi, R. (2022). A strawberry harvest aiding system with crop transport collaborative robots: Design, development, and field evaluation. Journal of Field Robotics 39(8):1231-1257. https://doi.org/10.1002/rob.22106.

58. Popović, T., Krčo, S., Maraš, V., Hakola, L., Radonjić, S., Van Kranenburg, R., & Šandi, S. (2021). A novel solution for counterfeit prevention in the wine industry based on IoT, smart tags, and crowd-sourced information. Internet of Things 14(1):100375. https://doi.org/10.1016/j.iot.2021.100375.

59. Precedence Research (2024). Artificial intelligence (AI) in manufacturing market size, share, and trends. https://www.precedenceresearch.com/artificial-intelligence-in-manufacturing-market?utm_source=chatgpt.com. Accessed March 22, 2025.

60. Research and Markets (2024). https://www.researchandmarkets.com/report/united-states-agriculture-ai-market?utm_source=chatgpt.com. Accessed March 22, 2025.

61. Ryo, M. (2022). Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. Artificial Intelligence in Agriculture 6(1):257-265. https://doi.org/10.1016/j.aiia.2022.11.003.

62. Sachithra, V., & Subhashini, L. D. C. S. (2023). How artificial intelligence uses to achieve the agriculture sustainability: Systematic review. Artificial Intelligence in Agriculture 8(1):46-59. https://doi.org/10.1016/j.aiia.2023.04.002.

63. Modelling techniques to improve the quality of food using artificial intelligence. Journal of Food Quality 2021(1):2140010. https://doi.org/10.1155/2021/2140010.

64. Schimmelpfennig, D. (2016). Farm profits and adoption of precision agriculture. https://www.ers.usda.gov/publications/pub-details?pubid=80325. Accessed March 2, 2025.

65. Shrestha, A. "Multi-temporal UAV remote sensing combined with machine learning for estimating cotton yield." PhD diss., (Mississippi State University, 2024).

66. Silva, B., Nunes, L., Estevão, R., Aski, V., & Chandra, R. (2023). GPT-4 as an agronomist assistant? Answering agriculture exams using large language models. arXiv:2310.06225v2 [cs.AI]. https://doi.org/10.48550/arXiv.2310.06225.

67. Sparrow, R., Howard, M., & Degeling, C. (2021). Managing the risks of artificial intelligence in agriculture. NJAS Impact in Agricultural and Life Sciences 93(1):172–196. https://doi.org/10.1080/27685241.2021.2008777.

68. Stevens, A. (2025). Artificial intelligence and cybersecurity: the future of grain farming. https://www.extension.iastate.edu/agdm/articles/others/SteFeb25.html. Accessed February 23, 2025.

69. Strong, R., Sprayberry, S. Dooley, K., Ahn, J., Richards, J., Kinsella, J., Lee, C.-L., Ray, N., Cardey, S., Benson, C., & Ettekal, A. (2023). Sustaining global food systems with youth digital livestock production curricula interventions and adoption to professionally develop agents of change. Sustainability 15(18):13896. https://doi.org/10.3390/su151813896.

70. Subeesh, A., & Mehta, C. R. (2021). Automation and digitization of agriculture using artificial intelligence and internet of things. Artificial Intelligence in Agriculture 5(1):278–291. https://doi.org/10.1016/j.aiia.2021.11.004.

71. Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture 4(1):58–73. https://doi.org/10.1016/j.aiia.2020.04.002.

72. Taseer, A., & Han, X. (2024). Advancements in variable rate spraying for precise spray requirements in precision agriculture using unmanned aerial spraying systems: A review. Computers and Electronics in Agriculture 219(1):108841. https://doi.org/10.1016/j.compag.2024.108841

73. Tedeschi, L. O. (2019). ASN-ASAS symposium: Future of data analytics in nutrition: Mathematical modeling in ruminant nutrition: Approaches and paradigms, extant models, and thoughts for upcoming predictive analytics. Journal of Animal Science 97(5):1321-1944. https://doi.org/10.1093/jas/skz092.

74. Tedeschi, L. O., Greenwood, P. L., & Halachmi I. (2021). Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming. Journal of Animal Science 99(2):1-11. https://doi.org/10.1093/jas/skab038.

75. Tedeschi, L. O. (2022). ASAS-NANP Symposium: Mathematical modeling in animal nutrition: the progression of data analytics and artificial intelligence in support of sustainable development in animal science. Journal of Animal Science 100(6):1-11. https://doi.org/10.1093/jas/skac111.

76. Tedeschi, L. O. (2023). Review: The prevailing mathematical modelling classifications and paradigms to support the advancement of sustainable animal production. Animal 17(1):100813. https://doi.org/10.1016/j.animal.2023.100813.

77. Trump, D. (2018). Executive Order 13821—Streamlining and expediting requests to locate broadband facilities in rural America. https://www.federalregister.gov/documents/2018/01/11/2018-00553/streamlining-and-expediting-requests-to-locate-broadband-facilities-in-rural-america. Accessed February 24, 2025.

78. United Nations (2025). Global issues: Population. https://www.un.org/en/global-issues/population#:~:text=Our%20growing%20population&text=The%20world's%20population%20is%20expected,billion%20in%20the%20mid%2D2080s. Accessed March 23, 2025.

79. USDA National Agricultural Statistics Service (2022). Census of Agriculture. https://www.nass.usda.gov/AgCensus. Accessed March 2, 2025.

80. USDA (2024). Biden-Harris administration connects people and businesses in rural areas to reliable high-speed internet in 18 states. https://www.usda.gov/about-usda/news/press-releases/2024/12/18/biden-harris-administration-connects-people-and-businesses-rural-areas-reliable-high-speed-internet. Accessed March 2, 2025.

81. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Fellander, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications 11(1):233. https://doi.org/10.1038/s41467-019-14108-y.

82. White, B. J., Amrine, D. E., and Larson, R. L. (2018). Big data analytics and precision animal agriculture symposium: Data to decisions. Journal of Animal Science 96(4):1531-1539. https://doi.org/10.1093/jas/skx065.

83. White, E. L., Thomasson, J. A., Auvermann, B., Kitchen, N. R., Pierson, L. S., Porter, D., ... & Werner, F. (2021). Report from the conference, "Identifying obstacles to applying big data in agriculture". Precision Agriculture 22(1):306-315. https://doi.org/10.1007/s11119-020-09738-y.

84. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming – A review. Agricultural Systems 153(1):69-80. https://doi.org/10.1016/j.agsy.2017.01.023.

85. Xu, W., Xu, T., Thomasson, J. A., Chen, W., Karthikeyan, R., Tian, ... & Su, Q. (2023). A lightweight SSV2-YOLO based model for detection of sugarcane aphids in unstructured natural environments. Computers and Electronics in Agriculture 211(1):107961. https://doi.org/10.1016/j.compag.2023.107961.

86. Yadav, P. K., Thomasson, J. A., Hardin, R., Searcy, S. W., Braga-Neto, U., Popescu, S. C., ... & White, E. L. (2023). Plastic contaminant detection in aerial imagery of cotton fields using deep learning. Agriculture 13(7):1365. https://doi.org/10.3390/agriculture13071365.

87. Yadav, P. K., Thomasson, J. A., Hardin, R., Searcy, S. W., Braga-Neto, U., Popescu, S. C., ... & Enciso, J. (2024). AI-based computer vision detection of cotton in corn fields using UAS remote sensing data and spot-spray application. Remote Sensing 16(15):2754. https://doi.org/10.3390/rs16152754.