POTENTIAL APPLICATIONS AND BENEFITS OF SMART FARM TECHNOLOGIES

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MS-Professional Paper
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Keywords: agriculture technology; artificial intelligence (AI); Farm Management Information System (FMIS); internet of things (IoT); precision agriculture

In the last 30 years there have been significant advances in technology that have made agricultural operations faster, more productive, and more efficient. There can be significant barriers to producer entry from the family farm scale, due to cost, accessibility, and the knowledge required to implement many of these technologies. Many of the technologies that can greatly improve a producer's operations are proprietary products that may only be usable in conjunction with expensive agricultural equipment or service providers. It is often not economically feasible for smaller operations to purchase the required equipment and accessories, which can cost hundreds of thousands of dollars. The initial investment required to implement precision agriculture technologies has been cited as a reason for farmers to be reluctant adopting them (Blasch 2020). There are technology options that can become effective elements of a farm management plan at every scale. From software to physical products, there are choices available to improve both crop and livestock operations. This report will review some prominent methods of data collection for agricultural enterprises and then go on to review tools that can be utilized to transmit and transform that data into a form that is valuable to the producer (Figure 1). Implementing IT related technologies for use in agricultural enterprises can increase profitability and efficiency to farmers of many different scales.

The Precision Agriculture Landscape

New products geared towards farming operations are coming onto the market rapidly as technology continues to improve and evolve. As a farm manager, it may become overwhelming to determine what products can serve to improve operational efficiency, profitability, and sustainability. It is important to evaluate the needs of a specific farm to determine which technologies are the best fit. There are many considerations that ought to be made before investing time and money in a new product for a farm. Cost, availability, climate, internet access, access to labor, and the type of farming operation and commodities are a few things that are important to consider before choosing a product.

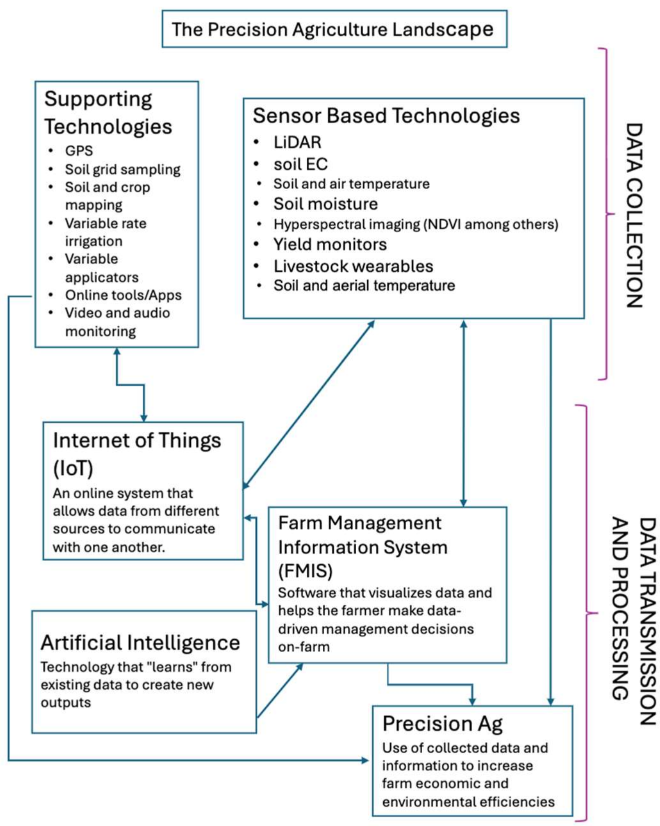

Figure 1. Overview of Smart Agriculture technologies covered in this report.

Figure 1 represents the precision agriculture landscape that can incorporate many types of technologies into a system for the collection, processing, and transmission of farm related data. Many of these technologies are dependent on and can be used in conjunction with one another. A typical farm that is using precision agriculture techniques will likely utilize many of the technologies and products listed here for their farm management purposes. Each farm’s practical implementation of precision agriculture technologies may vary greatly. On a very basic level, precision agriculture in the present day will generally consist of a variety of sensors for data collection, an internet connection and method to transmit data from the sensors where it was collected, and software program that stores the data and processes it or analyzes it into a form that the farmer can use.

Tools for Data Collection: In-field Sensors

Sensors are a cornerstone of precision agriculture, both for field monitoring and for the application of products. Sensors can be used to control the application rate of seed, water, fertilizer, pesticides, etc. and can be incorporated into traditional agricultural machinery to make it “smarter”. By applying amendments and products to the crop production system in an optimal way and analyzing data collected on a crop’s growth environment, growers can increase their profitability and sustainability through responsible resource management. These should be critical objectives for agriculture to help address the challenges that the world is facing via climate change and a growing population (Monteiro et al., 2021). Location sensors, or Global Positioning System (GPS) devices, are a critical part of many agriculture-specific IoT technologies (Elijah et al., 2018) and can provide additional value to other types of sensors when they are paired together. For example, a tractor with a variable rate sensor and a GPS sensor can collect valuable geospatial data in addition to application rate data that can then be sent to an

FMIS to be visualized on a map by a farmer. Location data from GPS sensors can be especially valuable to producers that are farming over expansive areas or with multiple employees to manage.

There are diverse ways to apply sensors into traditional agricultural farm machinery, such as seeders, tillers, tractors, combines, hay baling equipment, sprayers, spreaders, etc. A common application of integrating sensors with agricultural machinery is with variable rate technology (VRT). The system utilizes a previously created prescription or recommendation that communicates the rate of seed, fertilizer, or other product that needs to be applied across a predefined, mapped area, with the help of GPS for positioning across the field . In the context of VRT, a recommendation is a digital file that contains a target rate that should be applied to a field per zone (Šarauskis et al., 2022). In some cases, the required rate of application can be determined in real time by sensors installed on the machine. Rates are determined using a combination of soil data, terrain data, crop data from previous seasons, or other types of data (Monteiro et al., 2021). An example of VRT is precision seeding or variable rate seeding, where sensors are incorporated into a planter to control seed spacing and depth. This can optimize germination rates and plant spacing based on landscape conditions, potentially leading to greater yields. Variable rate seeding operations can be carried out based on different parameters of the area of interest, including soil conditions and nutrient profile, topography, and weather information. Seed drills are adjusted using preferred parameters and the integration of precise GPS sensors allows the operator to apply seed in a way that optimizes yield and minimizes waste (Šarauskis et al., 2022). Farmers can access variable rate technologies by visiting their local agricultural machinery dealerships where they can learn about pricing, installation, and how to use the technology.

Sensors that monitor a crop's growing environment, such as humidity, light intensity, soil conditions, and weather conditions can provide critical information to allow a grower to improve their yield and crop quality (Garlando et al., 2020). Different types of soil sensors can monitor soil conditions to help producers make decisions about tillage, irrigation, nutrient management, and even whether to drive in the field to avoid compaction. Some of the main types of soil sensors monitor soil moisture, soil solute/salinity concentration (via electrical conductivity sensors), soil clay and organic matter content, and soil nutrient concentrations (Monteiro et al., 2021).

A commonly used soil moisture sensor on some small farms is a Watermark™ sensor that is used to guide farmers with irrigation timing (Figure 2).

Figure 2. 900M datalogger (left) and Watermark sensor (right). (Dong et al., 2020)

Watermark™ sensors (Irrometer, Riverside, CA) are affordable compared to other sensor options. They can be used to take individual measurements in a field using a handheld reader or they can be left in the field to record data continuously when paired with a data logger

(Thompson et al., 2006). This sensor type contains a granular matrix that can measure changes in soil matric potential. According to Dong et al. (2020), soil matric potential is the "physical force required for the plant to move water into its root system." Watermark sensors work by monitoring changes in soil tension, which in turn provides information about soil moisture by providing a value from 0 to -239 kPa, with 0 kPa indicating the soil is fully saturated. University extension irrigation guidelines help growers to determine the amount of water they need to apply based on the values returned from their readers or loggers and based on their soil type (Dong et al., 2020). While soil moisture, electrical conductivity, and temperature can be collected real-time using relatively inexpensive sensor options, more complex and comprehensive soil chemical testing is usually achieved through manual soil collections and analysis using university or commercial labs.

Plant focused sensors assess potential crop health, allowing farmers to quickly respond to plant stressed caused by environmental conditions, pest and disease pressures. Plant focused sensors may also have post-harvest applications when it comes to determining produce quality, moisture percentages of grains, etc. Imagery based sensors and VOC (Volatile Organic Compound) detecting sensors provide important information about plant health and crop quality. Plant imaging can help with field scouting by locating with high accuracy where plant stress from environmental conditions and diseases might exist within a field. For example, Normalized Differential Vegetative Index (NDVI) is a widely used metric to monitor crop and plant health (Garlando et al., 2020). NDVI "is a measure of the ratio of reflectance in the near infra-red (NIR) and red wavebands" according to Stamford et al. (2023). Data utilized for NDVI calculations is typically collected through spectral imaging devices. The cause of stress often still requires interpretation by the farmer of service provider. There are many different types of these devices on the market, and they can vary greatly in price. For example, spectral imagery through drone technology will typically be more expensive than tractor attachments, and especially hand-held devices. It is common for these devices to cost from $2000 to $5000. There are less expensive devices available, but they may not provide data that are as accurate or cover an adequately large growing area as compared to some of the more sophisticated devices. Stamford et al. (2023) proposed a design for an effective low-cost system for farmers to calculate NDVI using a Raspberry Pi (a simple computer) and digital cameras. Solutions like this, while affordable, involve sourcing materials and assembling the system, and this may be a barrier to some farmers that do not possess these technical skills. Another potential challenge associated with spectral imaging is the transfer and interpretation of data after it is collected (Stamford et al., 2023).

Tools for Data Collection: Livestock Sensors

As countries continue to become wealthier and populations increase, global animal product consumption is expected to increase by 70% by 2050 (Berckmans 2017). This increased demand for animal products is expected to increase the density of livestock on farms, especially as the number of farmers and individual farms are decreasing. Higher concentrations of livestock and poultry on farms present risks to human and animal health, especially through diseases (including zoonotic diseases). On top of this, concentrated animal populations can increase the risk of antibiotic resistance when animals are consistently given antibiotics over time to mitigate disease. Concentrated livestock and poultry farms also present environmental problems (Berckmans 2017) like nutrient runoff from improperly managed animal waste. It has been estimated that animal agriculture contributes to 14.5% of anthropogenic greenhouse gas emissions globally (Kristiansen, et. al 2021). The increased demand for animal products along with the industry's contribution to climate change make it critical for farmers to manage their operations in a way that is efficient, ecologically sound and with as little waste as possible. Precision Livestock Farming (PLF) is a tool that may be able to alleviate some of the concerns that scientists predict farmers will face in the next 25 years or so.

Precision Livestock Farming is a method of farming that incorporates a variety of data types (usually collected from sensors, cameras, or microphones) to aid with the management of livestock and poultry operations. Precision livestock technologies can be an important factor in monitoring animal health, weight gain, behavioral patterns, location, and potential environmental impacts of livestock operations (Berckmans 2017). Sensors can provide a lot of critical information related to animal welfare. They can quickly and remotely alert the producer (via a connection to a web application) to changes in animal behavior that may indicate that further intervention is needed (Džermeikaitė et al., 2023). An example of this is through biometric sensing. Biometric sensing is an umbrella term for a variety of technologies that monitor behavioral and biological functions of livestock. Biometric sensing has become commonplace on many farms to reduce the labor associated with monitoring animal wellbeing on a large scale (Neethirajan and Kemp 2021).

Thermal infrared imaging is a type of biometric sensing that can measure an animal(s) temperature without coming into physical contact with the animal itself (Neethirajan and Kemp 2021). Thermal imaging is done through the installation of cameras in the livestock's environment. It works by detecting infrared radiation that is released from the animal's surface. This results in several practical applications for livestock farmers. For example, the temperature distribution of an animal's body can be used to make inferences about its stress level and potential illnesses (direct indicators of animal wellbeing) by identifying changes in blood flow. It can also be used as an estrus detection tool and to monitor how efficiently an animal can metabolize feed (de Alencar Nääs et al., 2014). Sensors may be connected to software applications via the internet, allowing data to be easily accessible by users, even when they are far away from their farm. On farms of all scales, monitoring each animal can help to ensure the health and welfare of the animal which in turn ensures higher profits for the producer, and a quality product for the end customer.

Dairy operations have some unique considerations that need to be made when considering the implementation of PLF technologies. Part of the reason for this is that a very perishable product (milk) is being introduced into the farm management plan that requires additional monitoring and logistical considerations. Tracking reproductive cycles is also another important consideration for dairy (and other types of livestock) farms as they have important implications for the yearly schedules and profitability of operations. Many livestock sensors on the market today can be used to track the menstrual cycle of animals to optimize breeding practices. According to Kaur et al., there are already some commonly used PLF technologies on dairy farms, including monitoring systems for “daily milk production, milk composition, activity, cow body temperature, milk conductivity, estrus detection monitoring, and daily body weight.” Automated milking systems are another time saving technology that can greatly benefit dairy operation (Kaur et al., 2023). Robotic milking systems can reap huge labor savings for a dairy farm but purchasing them is a big financial risk due to their high cost of installation. Recent advances in automated milking systems integrate sensors that can collect data on milk quality and the health of the cow during milking. The integration of predictive modeling (a type of artificial intelligence) with data collected from automatic milking systems can help dairy farmers make improved operational decisions. This type of modeling can provide better insights to the farmer about the health of the cow, milk yields, and milk quality (Ji et al., 2022).

Most PLF relies on continuous monitoring of individual animals or populations of animals. 24/7 monitoring allows producers to identify when there is a significant change in an animal's health that may need attention. This may be identified through the monitoring of a vital sign like temperature or heart rate, or activity level. Live monitoring is important because a change in the animal's vital signs or behavioral patterns can occur very quickly in the event of an illness or injury. Precision livestock technology can provide value in many ways including detection of illness at an early stage, precisely calculating the amount of feed needed for desired weight gain, and more (Berckmans 2017). The ability for precision livestock farms to remotely monitor animal stress or wellbeing using a small amount of human labor has the potential to improve animal welfare and allow producers to make management decisions based on that data. This is something that consumers demand and therefore, it can create opportunities for farmers to command a higher price for their products compared to producers not using these technologies \ (Kaur et al., 2023) through animal welfare related or organic certifications.

Some challenges exist when collecting data on livestock. The data collected through sensors is only beneficial to the producer if there is a way to analyze it and use it for decision making. Additionally, data may come in different forms and from different platforms, making it difficult to analyze information, even though it may still be important to the operation (Lovarelli et al., 2020). An example of a challenge with data collected through PLF is The European Union Precision Livestock Farming Project which monitored fattening periods for pigs for three years and yielded 120 terabytes of imagery alone (not including the sound data that was also collected) (Berckmans 2017). The enormous amount of data collected through PLF (especially on animals with a long lifespan) can be difficult for existing IT infrastructure to handle. Additionally, most of the data that is collected is rather insignificant, until there is a drastic change (like a sudden increase in heart rate) or emergency that causes one of the parameters to drastically shift (Kaur 2023). It is important for producers to use programs that utilize algorithms to help filter out or "clean" the data that is collected so that it can be presented to the producer in a format that is valuable to them. This data may then be presented to the farm manager through a software program (via a web or mobile application) with a user interface where they can use the cleaned data to make management decisions.

Tools for Data Collection: Digital Mapping in Agriculture

Light Detection and Ranging (LiDAR) technologies utilize lasers and sensors to collect elevation data across a target area (Huang et al., 2022). LiDAR plays an important role in agriculture due to its versatility, ability to cover large areas of land, and noninvasive methods of collecting data. The technology was used initially in the United States in the 1970s by the aerospace industry (Rivera et al., 2023). Its application was invaluable for geologists for mapping the Earth's surface and more recently its use has expanded into many different industries, including hydrology, surveying, construction, architecture, archeology, self-driving cars and agriculture. LiDAR is non-intrusive and data collection can be collected day or night, since radiation does not negatively impact its operation.

LiDAR systems can be either land or air based. Land-based systems can include a stationary sensor setup (such as a tripod) or can be attached to a moving vehicle or tractor. Air based systems are generally installed on drones or aircraft (Debnath et al., 2023) According to Debnath et al. (2023), "Most airborne LiDAR systems consist of LiDAR sensors, data storage devices, an on-board computer, a global positioning system (GPS) and an inertial measurement unit (IMU)." Land based LiDAR systems can have valuable applications in areas where aircraft are not allowed or able to access (Debnath et al., 2023).

LiDAR sensors work by releasing “pulsed light waves” that hit nearby objects and then return to the sensor. The x, y, z location of the surface is calculated using the speed of light, the travel time for a given pulse to return to the sensor, the direction of the pulse, and the exact x,y, and z location of the sensor (Debnath et al., 2023). The number of sensors employed in a LiDAR system and the density of light pulses can impact the quality of the data collected. Data collected from the system is stored in a “point cloud” (Rivera et al., 2023). LiDAR data usually provides value to an end user through the creation of 3D models that are created with the addition of data from other technologies (Rivera et al., 2023).

LiDAR can be used for many different types of valuable data collection in agriculture. For example, LiDAR can help determine soil characteristics, topography, leaf area index (LAI), crop health and growth, and spray drift for agricultural products. LiDAR can detect variation in a landscape, which is helpful for many different land management purposes, including for measuring crop or plant height (Rivera et al., 2023). One important application of LiDAR in agriculture is the use of LiDAR data to map the location and flow of water in a field (Debnath et al., 2023). This is very valuable data for crop and livestock producers but is especially useful for planning irrigation or estimating yield and disease pressure from a given area in a plot. LiDAR can also be utilized in orchards and vineyards to help determine a plan for pruning so that the appropriate light penetration through the canopy occurs(Rivera et al., 2023).

Something to consider before investing in LiDAR technology is the quality and processing of the data that will be collected. For the best results, high resolution images must be obtained and an accessible way to present the data to the end user must be available. According to Debnath et al., there are still developments that need to be made for affordable and accurate software programs to become available to LiDAR users for data analysis. Some LiDAR systems struggle to differentiate between weeds and crops in a field. This is very problematic for most agricultural contexts when someone is using this technology to help determine plant growth, yield, height, or biomass of the crop that is planted (Debnath et al., 2023). Different machine learning techniques can be applied to LiDAR data to help filter out important data and improve the quality of data so that it is more useful to the end user (Huang, et al., 2022). Another drawback of LiDAR is that its implementation can be costly, especially for more advanced imagery collection and quality. Many farmers may see this as a barrier to utilizing the technology in their operations (Rivera et al., 2023), but aerial images can be very valuable to a crop producer, especially those on a larger scale that may be limited in their ability to frequently monitor their entire growing area (Monteiro, et al., 2021).

Tools for Data Transmission and Management: Internet of Things (IoT)

The Internet of Things (IoT) is a network of different devices that utilize the internet to collect data and to transmit information between one another, through unique identifiers (UIDs) (Elijah et al., 2018). The main features of the IoT are a wireless internet connection, a data collection method (mainly via sensors), a modem to communicate to the cloud, and a mechanism to process and store data (Bulut & Wu 2024). Data storage is through what is known as a "data lake." Data is oftentimes delivered to an end-user through a user interface where the data may be further analyzed by the program to provide additional information to the user. In an agricultural context, IoT usually utilizes 4 steps to get data to the end user. According to Elijah et al. (2018), these four steps are:

1. Data collection
2. Data transfer to IoT devices
3. Data and image analyses
4. Visualize and manage a field operation via an app

From a broad perspective, the IoT can provide several important benefits to a variety of industries including improving efficiency and management decisions (Misra et al., 2022). IoT technology adoption in agriculture can lead to improved yields, increased profits, more sustainable production practices, and improved human health impacts from increased food security and environmental benefits (Bulut & Wu 2024). In addition to directly impacting crop and livestock production, IoT systems can serve as an important tool for planning, logistics, postharvest handling, and transportation. When these things become more efficient, sustainability and profitability can be positively impacted. An example of this might be reduced fuel usage when someone operating a tractor uses IoT enabled devices to choose the best route for driving to their work for the day. Small changes in daily, repetitive tasks that are done frequently may reap large time and fuel saving benefits over time for an operation. With consumers demanding more transparency around the production and distribution practices of their food, farmers can provide valuable data to consumers at every step of the supply chain. IoT can provide data about every place their food has been, from farm to table, so that consumers can be confident about the safety of an agricultural product. For example, a grower can provide confidence to consumers that their produce was not affected by some kind of foodborne illness outbreak because they can prove the origin of the product using data collected via IoT. This may provide additional value to the consumer and profit to the producer (Elijah et al., 2018).

IoT technology can be particularly powerful to producers when it is paired with agricultural machinery. In crop production systems, tractors, sprayers, combines, and other types of agricultural machinery can be integrated into an IoT network. These smart machines can improve the efficiency and quality of many different agricultural field operations including tillage, planting, spraying, spreading, and harvesting. IoT is the mechanism that allows GPS sensors to communicate with a VRT sensor on a planter so that planting rate data is associated with geospatial data, as discussed previously. It is also the mechanism that communicates the data collected from field tasks to the end user via a web or mobile application and vice versa. IoT solutions are becoming more widely available for traditional agricultural machinery, robots, and unmanned aerial vehicles (UAVs) (Elijah et al., 2018).

There are a variety of challenges that may hinder IoT technology adoption by farmers. Barriers that exist are different regionally and depend on which technologies are available and the legal status of technologies in different countries. Data security and privacy is a developing field for IoT systems which may be a concern to farmers (Elijah et al., 2018). Security threats can also exist and be costly when autonomous machinery and implements are a part of an IoT system due to the huge impact that impaired GPS systems and sensors can have on autonomous field operations (Demestichas et al., 2020). Another major challenge of IoT adoption includes the initial financial investment required and for certain IoT technologies, especially those that require newer tractors to function. Costs vary greatly depending on the operation size and technology being purchased, but hardware required for the system can incur a large up-front cost. Additionally, the cost of internet service and network access can be beyond the reach of some growers (Elijah, et al. 2018).

Tools for Data Transmission and Management: Artificial Intelligence (AI)

In general, artificial intelligence refers to algorithms in machines or devices that can perform a new service or action based on patterns learned from previous data (Smith 2020). For example, in machine learning, a field of AI, prediction models are made by taking a dataset which contains multiple parameters and known outcomes and breaking it into training, validation, and testing datasets. First, the model makes predictions on the training data, then the model’s predictions are evaluated against the validation dataset. If the model performed poorly with the validation data, it is revised and re-trained by the training data. This process is repeated until the performance reaches a predetermined acceptable level. Then, the final performance is evaluated again using the testing dataset (Genç & Tunç, 2019). After training, validating, and testing the AI model can be used on novel data to make predictions.

Agricultural enterprises are excellent candidates for the application of artificial intelligence due to the complex nature of their operations. The constantly changing input of various types of data (weather, soil conditions, crop health, animal health, etc.) can make management and decision-making challenging for producers. Additionally, many farms cover a large amount of acreage and exist in remote, difficult to access areas. Remote monitoring in conjunction with AI can be a very powerful tool for managing large acreage without having to spend significant time and labor to monitor various land tracts. Because agriculture is so weather and climate dependent, AI can also inform decision making (Smith 2020). This will become increasingly important as the climate continues to change.

Figure 3 represents four types of artificial intelligence analytical methods which describe how AI can be used and to which degree human intelligence is required (Smith 2020). Descriptive analytics is the simplest form of analysis, which only summarizes or describes data and involves the largest need for human intelligence to make decisions. Diagnostic analytics identifies patterns in data and can be used to hint at causality with the help of human intelligence. AI predictive analytical methods also find patterns in data but can make predictions in addition to identifying them. Finally, AI prescriptive analytical methods find patterns in the dataset, but can also find solutions to the problems as well. Unlike the other analytical methods, prescriptive

AI can be configured to make decisions automatically based on the solutions it finds without human intervention (Smith 2020).

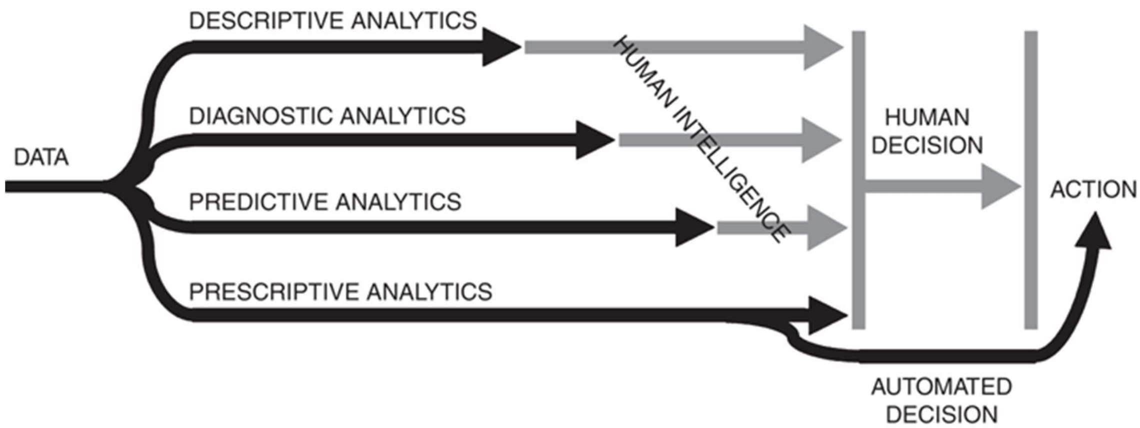

Figure 3. AI can be represented by different computational analytic categories that then require different degrees of human processing prior to reaching a final action (Smith 2020)

Applying the AI analytical methods from Smith (2020) would give the following examples in livestock farming. Using computer vision to count livestock (Sarwar et al., 2018) is one example of using descriptive AI, while detecting illnesses such as mastitis using milk measurements from automated milking systems (AMS) is a diagnostic use of AI (Ozella et al., 2023). In both cases, a lot of human decision making is still required, such as determining what conclusions to draw from livestock counts or determining how to treat a given illness. Utilizing machine learning on cow behavior, health, milk quality and environmental conditions to predict future milk yield, is an example of predictive AI. The recommendation or implementation of mitigating actions is an example of prescriptive AI (Ji et al., 2022). Additionally, various forms of agricultural data and imagery can be “cleaned” by using artificial intelligence to remove extraneous portions of the data or filtering the data. This allows for potentially more accurate and quicker analysis of the data, therefore providing additional value to the agricultural enterprise (Wongchai et al., 2022). The field of artificial intelligence is rapidly expanding and it can be challenging to utilize without specialized knowledge. However, more agricultural products and software systems are being developed that includes an AI component that does not require additional specialized knowledge by their users.

Tools for Data Transmission and Management: Farm Management Information Systems

FMISs originated as software programs for record keeping and data storage, but they have developed into complex programs that can now receive input from multiple sources and give producers accurate information and recommendations to make management decisions on (Melzer et al., 2023). A Farm Management Information System (FMIS) is a web, mobile, or desktop application that can provide a variety of valuable services to a producer. FMIS Programs are software programs that store data in a database, process it, and then present it to an end user through a user interface that is typically branded. An FMIS can be accessed through a variety of formats such as on a desktop computer, a tablet, or by a web application accessed through a smartphone. The FMIS may work in conjunction with various types of agricultural machinery or hardware products, or it can also exist as a standalone software program. Many of the technologies previously discussed can integrate with and feed data into an FMIS. While many FMISs require upfront payment or a monthly subscription fee, there are also university and non-profit FMIS resources that are available to producers for free or at a low cost. Most FMIS programs allow data to be stored and easily displayed to users (through a user interface). They can meet the management and planning needs of both livestock and crop producers. FMIS programs can be used to visualize and organize many different types of data including agronomic, operational, animal health, weather, financial, and more.

FMIS programs help address various farm goals, such as helping the operator to comply with environmental and legal regulations, maintain health and safety of workers, increase profitability of the farm business, maintain records from year to year, and maintain a quality agricultural product (Fountas et al., 2015). FMIS programs can serve as an important resource for complying with state and federal regulations surrounding restricted use agricultural products like some pesticides. For example, a crop producer might be able to use data in an FMIS to show that the wind and weather conditions were within a required parameter when they applied a certain chemical to a field. Many grants and subsidies are provided to farms by governments on the basis that they are engaging in certain conservation, safety, or sustainability related practices on their farms. An example of this would be a USDA certified organic farm using an FMIS as a record keeping tool to show that the products that they have applied to their organic land are in compliance with organic standards. In the EU where sustainability expectations for farms are more advanced than in the US, it has also been suggested that certifying bodies can utilize FMIS programs to provide growers with data on the sustainability goals and metrics that they should be complying with (Poppe et al., 2024). A FMIS is an organized approach to storing and sharing data with program sponsors that have a vested interest in this information (Melzer et al., 2023).

FMIS programs can differ in available features. For example, some FMIS programs are comprehensive production and business management software programs, while others may be more specialized to a topic area, such as an FMIS that only keeps records of crop production activities and metrics in the field. When considering which FMIS to adopt for a farming operation, there are several things to consider, such as cost of implementation and maintenance, the type and size of the agricultural operation, number of employees of the farm, access to high-speed internet, business and financial goals, geographic location and personal preferences. Utilizing multiple different FMIS programs may be most suited to a producer's needs. Table 1 outlines some of the major FMIS programs that are on the market in the United States today and some of their major features. They share many core features in common and typically require the purchase of branded hardware (modems, sensors, or machinery) to access the full functionality of the system. Many of the programs provide free account creation so that a potential user can get acquainted with the software, but feature access is generally limited in the free versions.

Table 1. Commonly used FMIS Programs in the United States and their basic features

Program	Manufacturer	Cost	Purchase options	Website Link	Features	Notes
AFS/PLM Connect	CNH Industrial	Free	Online or via Case/New Holland Dealerships	AFS Connect, PLM Connect	Wireless data transfer, 3rd party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display, modem, and GPS receiver to collect and transmit agronomic data
Operations Center	John Deere	Free	Online or via John Deere Dealerships	John Deere Operations Center	Wireless data transfer, 3rd party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display, modem, and GPS receiver to collect and transmit agronomic data
Climate FieldView	Bayer	$0-$800/year	Online	Climate Website	Wireless data transfer, 3rd Party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display, modem, and GPS receiver to collect and transmit agronomic data
SMS	AgLeader	Limited free version Basic: $995/$260 Yearly Maintenance Fee Advanced: $2995/$775 Yearly Maintenance Fee	Through Reseller locations	SMS Website	Wireless data transfer, 3rd Party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display, modem, and GPS receiver to collect and transmit agronomic data
Trimble Ag Software	Trimble	Free	Via Trimble affiliated dealers, resellers, and service providers	Timble Website	Wireless data transfer, 3rd Party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display, modem, and GPS receiver to collect and transmit agronomic data
Slingshot*	Raven	Free	Via Raven dealership or online	Slingshot Website	Wireless data transfer, 3rd Party API Connections, Agronomic Data Visualization, Mobile App	Full functionality requires an in-cab display or iPad, modem, and GPS receiver to collect and transmit agronomic data

*Developed for Agricultural retailers

A significant benefit of an FMIS is the traceability of data from crop to crop or year to year. FMIS programs become more valuable to farmers over time as more data is added to the program since management practices can be compared year over year. A grower with access to multi-year data can make better decisions on varieties, and agronomic practices that can lead to greater yield and profitability. Some newer programs are even integrating artificial intelligence to improve data analysis (Kassahun et al., 2022). The future of FMIS will likely include the integration of even higher quality data collection over time and greater processing power to allow the producer to make better decisions for their operations (Fountas et al., 2015).

There are concerns from academics and farmers when it comes to storing large amounts of detailed agronomic data with a particular company through the use of their FMIS programs. Questions have been raised around the ethics of a company's potential use of the data that they have access to from users. An example of this would be companies using customer's data to try to sell them additional products, or modifying the price of their products based on where the customer is located geographically. The question of data ownership is a critical one in the discussion around data privacy from agronomic data, especially after data is processed using a company's proprietary technology (Sykuta 2016). Before agreeing to share agronomic or vehicle data with an FMIS, farmers should be sure to read the company's data privacy policy.

Conclusion

The precision agriculture landscape is complex and evolving, integrating technologies like sensors, wireless internet connection, artificial intelligence, digital mapping, diverse software programs, and more. Many of these technologies become even more powerful when combined with one another; however, issues around data compatibility and data transfer can make their integration challenging. New products and services developed for farming operations are coming onto the market rapidly as technology continues to improve and evolve. As a farm manager, it might seem overwhelming to determine what products best serve to improve operational efficiency, profitability, and sustainability. There are many considerations that ought to be made before investing time and money in a new product or management system for a farming operation. Cost, availability, complexity, climate, internet access, access to labor, scalability and the type of operation are a few things that are important to consider before choosing a product or service. The precision agriculture options available in the future will likely continue to improve and evolve to address agriculture's largest challenges like climate change, farm profitability, and feeding a growing, global population.

References

AFS Connect Farm | Get More Done Each Day | Case IH. (2024). AFS Connect Farm | Get More Done Each Day | Case IH. Case IH. Retrieved July 24, 2024, from https://www.caseih.com/en-us/unitedstates/products/precision-technology/afs-connect/afs-connect-farm

Berckmans, D. (2017). General introduction to precision livestock farming. *Animal Frontiers*, *7*(1), 6–11. https://doi.org/10.2527/af.2017.0102

Blasch, J., Van der Kroon, B., Van Beukering, P., Munster, R., Fabiani, S., Nino, P., & Vanino, S. (2020). Farmer preferences for adopting precision farming technologies: A case study from Italy. *European Review of Agricultural Economics*, *49*(1), 33–81. https://doi.org/10.1093/erae/jbaa031

Bulut, C., & Wu, P. F. (2024). More than two decades of research on IoT in agriculture: a systematic literature review. Internet Research, 34(3), 994–1016. https://doi.org/10.1108/INTR-07-2022-0559

FieldView Brochure – Turn your field data into insights. FieldView Brochure – Turn your field data into insights. Climate Field View. Retrieved July 24, 2024. https://fieldviewbrochure.com

Frequently Asked Questions | Operations Center | John Deere US. (n.d.). Frequently Asked Questions | Operations Center | John Deere US. John Deere. Retrieved July 24, 2024, from https://www.deere.com/en/technology-products/precision-ag-technology/operations-center/faq/

Genç, B., Tunç, H. (2019). Optimal training and test sets design for Machine Learning. Turkish Journal of Electrical Engineering & Computer Sciences, 27(2), 1534–1545. https://doi.org/10.3906/elk-1807-212

de Alencar Nääs, I., Garófallo Garcia, R., & Caldara, F. R.. (2014). Infrared thermal image for assessing animal health and welfare. 2(3). https://www.wellbeingintlstudiesrepository.org/cgi/viewcontent.cgi?article=1019&context=assawel

Debnath, S., Paul, M., & Debnath, T. (2023). Applications of LiDAR in Agriculture and Future Research Directions. *Journal of Imaging*, *9*(3), 57. https://doi.org/10.3390/jimaging9030057

Demestichas, K., Peppes, N., & Alexakis, T. (2020). Survey on Security Threats in Agricultural IoT and Smart Farming. Sensors (Basel, Switzerland), 20(22), 6458-. https://doi.org/10.3390/s20226458

Dong, Y., Miller, S. A., & Kelley, L. (2020). Improving Irrigation Water Use Efficiency: Using Soil Moisture Sensors. Michigan State University Extension. https://www.egr.msu.edu/bae/water/irrigation/sites/default/files/content/E3445_Improving%20Irrigation%20Water%20Use.pdf

Džermeikaitė, K., Bačėninaitė, D., & Antanaitis, R. (2023). Innovations in Cattle Farming: Application of Innovative Technologies and Sensors in the Diagnosis of Diseases. *Animals*, *13*(5), 780. https://doi.org/10.3390/ani13050780

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. H. D. N. (2018). An Overview of Internet of Things (IOT) and Data Analytics in Agriculture: Benefits and challenges. *IEEE Internet of Things Journal*, *5*(5), 3758–3773. https://doi.org/10.1109/jiot.2018.2844296

Ji, B., Banhazi, T., Phillips, C. J. C., Wang, C., & Li, B. (2022). A machine learning framework to predict the next month's daily milk yield, milk composition and milking frequency for cows in a robotic dairy farm. Biosystems Engineering, 216, 186–197. https://doi.org/10.1016/j.biosystemseng.2022.02.013

Garlando, U., Bar-On, L., Avni, A., Shacham-Diamand, Y., & Demarchi, D. (2020). Plants and Environmental Sensors for Smart Agriculture, an overview. *2020 IEEE SENSORS*. https://doi.org/10.1109/sensors47125.2020.9278748

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J., & Tisserye, B. (2015). Farm management information systems: Current situation and future perspectives. Computers and Electronics in Agriculture, 115, 40–50. https://doi.org/10.1016/j.compag.2015.05.011

Huang, S., Liu, L., Fu, X., Dong, J., Huang, F., & Lang, P. (2022). Overview of LiDAR Point Cloud Target Detection Methods Based on Deep Learning. *Sensor Review*, *42*(5), 485–502. https://doi.org/10.1108/sr-01-2022-0022

Kassahun, A., Bloo, R., Catal, C., & Mishra, A. (2022). Dairy Farm Management Information Systems. Electronics (Basel), 11(2), 239-. https://doi.org/10.3390/electronics11020239

Kaur, U., Malacco, V. M., Bai, H., Price, T. P., Datta, A., Xin, L., Sen, S., Nawrocki, R. A., Chiu, G., Sundaram, S., Min, B.-C., Daniels, K. M., White, R. R., Donkin, S. S., Brito, L. F., & Voyles, R. M. (2023). Invited Review: Integration of Technologies and Systems for Precision Animal Agriculture—a Case Study on Precision Dairy Farming. *Journal of Animal Science*, *101*. https://doi.org/10.1093/jas/skad206

Kristiansen, S., Painter, J., & Shea, M. (2020). Animal Agriculture and Climate Change in the US and UK Elite Media: Volume, responsibilities, causes and solutions. *Environmental Communication*, *15*(2), 153–172. https://doi.org/10.1080/17524032.2020.1805344

Lovarelli, D., Bacenetti, J., & Guarino, M. (2020). A Review on Dairy Cattle Farming: Is Precision Livestock Farming the Compromise for an Environmental, Economic and Social Sustainable Production? *Journal of Cleaner Production*, *262*, 121409. https://doi.org/10.1016/j.jclepro.2020.121409

Melzer, M., Bellingrath-Kimura, S., & Gandorfer, M. (2023). Commercial farm management information systems - A demand-oriented analysis of functions in practical use. *Smart Agricultural Technology*, *4*, 100203. https://doi.org/10.1016/j.atech.2023.100203

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 of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/jiot.2020.2998584

Monteiro, A., Santos, S., & Gonçalves, P. (2021). Precision Agriculture for Crop and Livestock Farming—Brief Review. *Animals*, *11*(8), 2345. https://doi.org/10.3390/ani11082345

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

Ozella, L., Brotto Rebuli, K., Forte, C., & Giacobini, M. (2023). A Literature Review of Modeling Approaches Applied to Data Collected in Automatic Milking Systems. *Animals: an open access journal from MDPI*, *13*(12), 1916. https://doi.org/10.3390/ani13121916

Poppe, K. J., Vrolijk, H. C. J., & van Asseldonk, M. A. P. M. (2024). Innovation in the Farm Office for Smart Sustainability Reporting. EuroChoices. https://doi.org/10.1111/1746-692X.12427

Rivera, G., Porras, R., Florencia, R., & Sánchez-Solís, J. P. (2023). LiDAR Applications in Precision Agriculture for Cultivating Crops: A review of Recent Advances. *Computers and Electronics in Agriculture*, *207*, 107737. https://doi.org/10.1016/j.compag.2023.107737

Raven Industries | Slingshot® Connectivity & Logistics. (2024, July 24). Raven Industries | Slingshot® Connectivity & Logistics. Raven. https://ravenind.com/products/connectivity-logistics/slingshot

Šarauskis E, Kazlauskas M, Naujokienė V, Bručienė I, Steponavičius D, Romaneckas K, Jasinskas A. (2022). Variable Rate Seeding in Precision Agriculture: Recent Advances and Future Perspectives. Agriculture. 12(2):305. https://doi.org/10.3390/agriculture12020305

Sarwar, F., Griffin, A., Periasamy, P., Portas, K., & Law, J. (2018). Detecting and counting sheep with a convolutional neural network. 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). https://doi.org/10.1109/avss.2018.8639306

Smith, M. J. (2020). Getting value from Artificial Intelligence in Agriculture. *Animal Production Science*, *60*(1), 46. https://doi.org/10.1071/an18522

SMS Farming Software - Ag Leader Products. (2024, July 24). SMS Farming Software - Ag Leader Products. Ag Leader. https://www.agleader.com/farm-management/sms-software/

Stamford, J. D., Vialet-Chabrand, S., Cameron, I., & Lawson, T. (2023). Development of an Accurate Low Cost NDVI Imaging System for Assessing Plant Health. *Plant Methods*, *19*(1). https://doi.org/10.1186/s13007-023-00981-8

Sykuta, M. E. (2016). Big Data in Agriculture: Property Rights, Privacy and Competition in Ag Data Services. The International Food and Agribusiness Management Review, 19(A), 57–74. https://doi.org/10.22004/ag.econ.240696

Thompson, R., Gallardo, M., Agüera, T., Valdez, L., & Fernández, M. (2006). Evaluation of the Watermark sensor for use with drip irrigated vegetable crops. Irrigation Science, 24(3), 185-202. https://doi.org/10.1007/s00271-005-0009-5

Trimble Ag Software. (n.d.).Trimble Ag Software. Ptxtrimble. Retrieved July 21, 2024, from https://agriculture.trimble.com/en/products/software/trimble-agriculture-software

Wongchai, A., Shukla, S. K., Ahmed, M. A., Sakthi, U., Jagdish, M., & kumar, R. (2022). Artificial Intelligence - Enabled Soft Sensor and Internet of Things for Sustainable Agriculture Using Ensemble Deep Learning Architecture. *Computers and Electrical Engineering,* 102, 108128. https://doi.org/10.1016/j.compeleceng.2022.108128