USDA Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

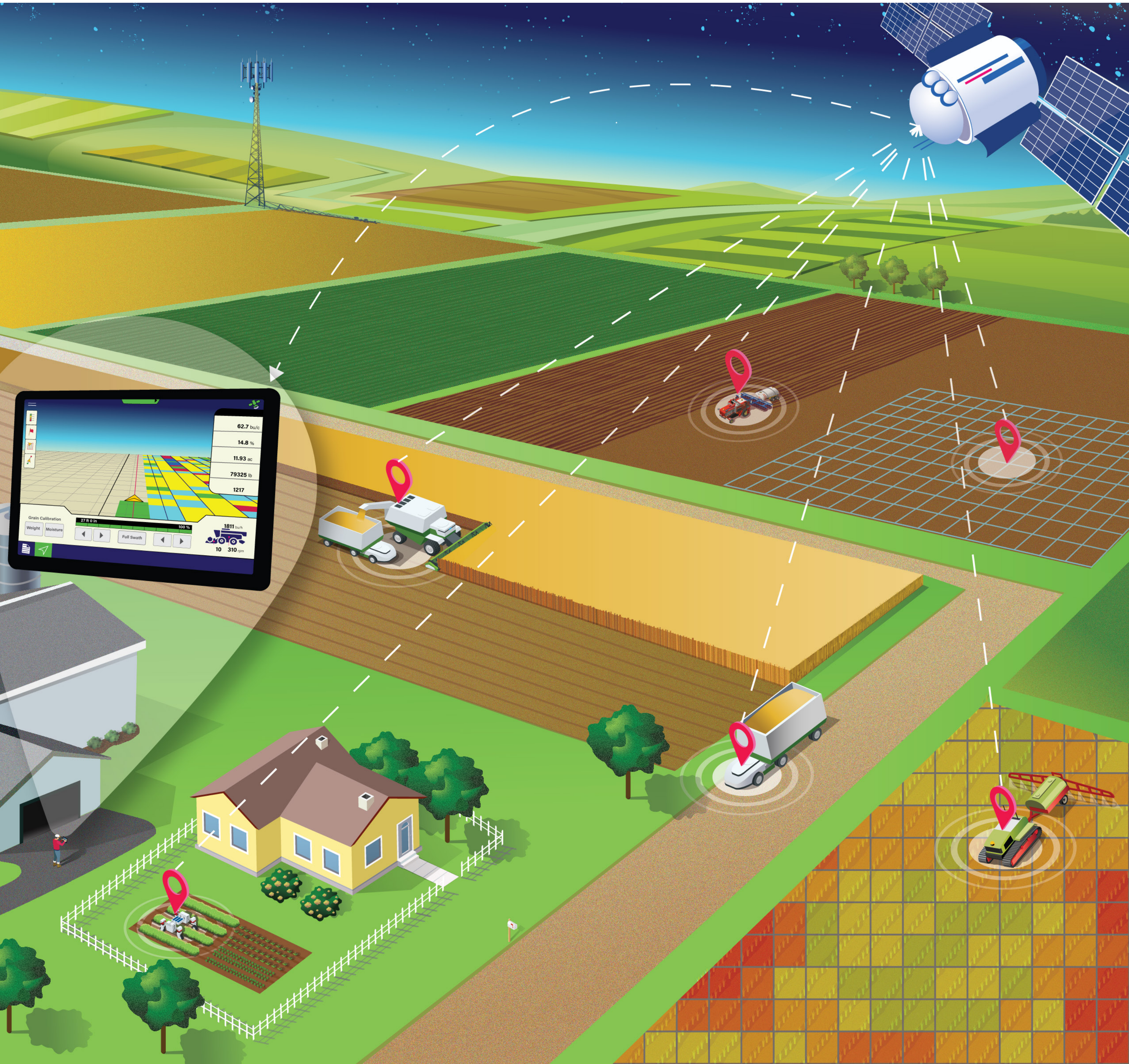
Economic Research Service

Economic Information Bulletin Number 248

February 2023

Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms

Jonathan McFadden, Eric Njuki, and Terry Griffin

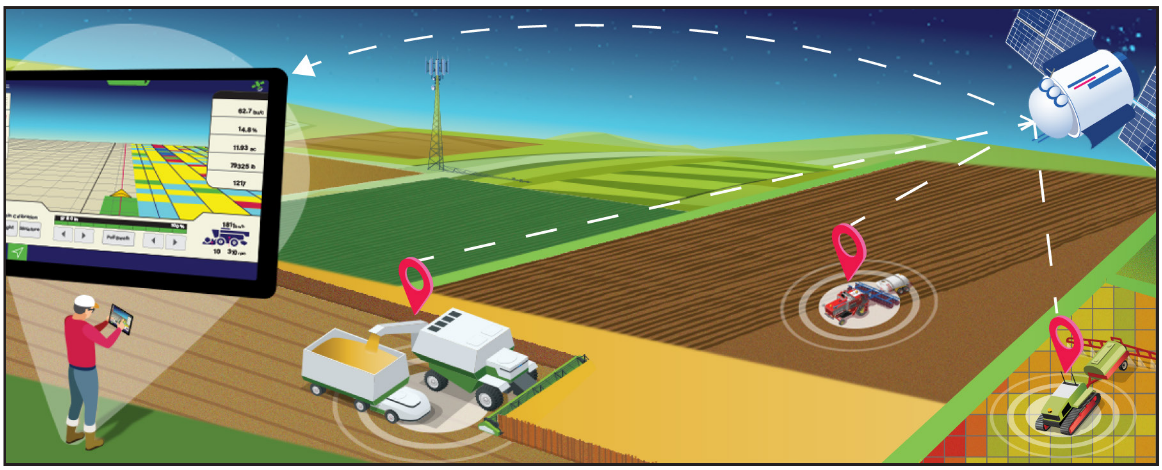


Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

Economic Research Service
www.ers.usda.gov

Recommended citation format for this publication:

Jonathan McFadden, Eric Njuki, and Terry Griffin. February 2023. *Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms,* EIB-248, U.S. Department of Agriculture, Economic Research Service.



USDA Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

Economic Research Service

Economic Information Bulletin Number 248

February 2023

Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms

Jonathan McFadden, Eric Njuki, and Terry Griffin

Abstract

Digital agriculture (DA)—the ongoing transformation of farming that includes digitalization and automation of farming tasks, of which precision agriculture (PA) is a chief element—may be an important part of the solution to several challenges facing U.S. agriculture, including rising production costs, climate change, and labor shortages, among others. Adoption of digital technologies in row-crop production has generally increased since 1996, though use has varied widely by technology and crop. Using data from USDA's Agricultural Resource Management Survey (ARMS), we document trends in the adoption of digital agriculture technologies between 1996 and 2019, emphasizing changes after 2016. The adoption of yield maps and soil maps (i.e., maps that associate physical characteristics with geographic coordinates) and variable rate technologies (VRT), in addition to other technologies, has been substantial on corn and soybean acreage for many years. Though their use has been increasing in recent years, technologies such as yield maps, soil maps, and VRT have been adopted on only between 5 and 25 percent of total U.S. planted acreage for winter wheat, cotton, sorghum, and rice. However, adoption of automated guidance has increased sharply in the past 20 years, with application on well over 50 percent of the acreage planted to corn, cotton, rice, sorghum, soybeans, and winter wheat. Beyond documentation of trends, this report explores certain drivers of farmers' uptake—including pricing, soil variability, USDA programs, labor-saving benefits, expected productivity impacts, and availability of consultant services.

Keywords: digital agriculture, digital technologies, automated guidance, variable rate technologies, drones, yield maps, soils maps, precision farming, precision agriculture, sustainability, productivity, Agricultural Resource Management Survey (ARMS)

Acknowledgments

The authors thank Roger Claassen, USDA, Natural Resources Conservation Service, for valuable assistance with the RCA Data Viewer, and Brent Hueth, Thomas Worth, and Krishna Paudel of USDA, Economic Research Service, for providing feedback on a draft of this research. We also thank Roberto Mosheim (USDA, ERS), Madhu Khanna (University of Illinois Urbana-Champaign), Aditya Khanal (Tennessee State University), and reviewers at OCE, FPAC, and NRCS for technical peer reviews. Thanks also to ERS staff members Christopher Whitney and Courtney Knauth for editing the report and to Adele Wilcoxen for design and layout.

About the authors

Jonathan McFadden and Eric Njuki are research economists with USDA, Economic Research Service; Terry Griffin is an associate professor of agricultural economics at Kansas State University.

Contents

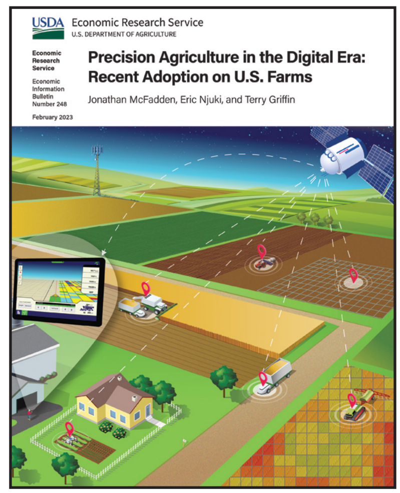
Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

A report summary from the Economic Research Service *February 2023*

Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms

Jonathan McFadden, Eric Njuki, and Terry Griffin

What Is the Issue?



The global population is projected to exceed 9.7 billion by 2050 (United Nations, 2022). This population growth will require substantial increases in food production, both in the United States and abroad, placing additional pressure on limited agricultural resources. Similarly, there are growing concerns about rising production costs, labor shortages, environmental changes, and unsustainability of intensive natural resources use in the U.S. farm sector. Public awareness of these issues has increased, leading to calls for the agricultural sector to develop innovative solutions. Digital agriculture (DA) provides an important opportunity to respond to several of these challenges.

DA technologies such as soil maps, yield monitors, yield maps, variable rate technologies (VRT), auto-steer and guidance systems, unmanned aerial vehicles, and satellite imagery have been available to farmers for several years. Adoption rates have varied considerably for wide-ranging reasons, including field topography and soil type, adjustment costs (e.g., subscription fees, training, maintenance, and replacement costs), and farmers' production scale and risk preferences. Adoption also varies by crop type and farmer socioeconomic characteristics. The benefits that accrue from adoption are numerous for most farmers and have been well documented.

As digital technologies and analytics continue to evolve, the digitalization of U.S. agriculture has become a major focus of the sector. Digitalization entails the use of data analytics, automated production processes, and development and commercialization of artificial intelligence applications. The potential to transform the U.S. agricultural sector by these technologies is considerable. Specifically, we expect that digitalization has the potential to increase efficiency in the farm sector—while contributing to cost reductions, yield increases, and/or enhancement to the well-being of farm operators. Although digitalization is a complex transformation with many components, it can be partly tracked by examining farmers' use of established and emerging technologies.

What Did the Study Find?

The report analyzes farmers' DA adoption rates for soil maps, yield maps, yield monitors, VRT, auto-steer and guidance systems, and aerial imagery across six major crops: corn, cotton, rice, sorghum, soybeans, and winter wheat.

- **A majority of row crop acreage is managed using auto-steer and guidance systems:** Auto-steer guidance systems were used on only 5.3 percent of planted corn acres in 2001, growing to 58 percent in 2016. Estimates for 2019 suggested 72.9-percent and 64.5-percent adoption rates for sorghum and cotton (planted acreage). In the same year, GPS applications were used on 40 percent of all U.S. farm and ranchland acreage for on-farm production.

- **Adoption rates vary by farm size:** At least half of relatively large row crop farms (those at or above the third quintile of acreage, i.e., with at least 60 percent of fields on farms with lower acreage) rely on yield maps, soil maps, VRT, and/or guidance systems. Meanwhile (except for cotton), less than 25 percent of smaller farms (those with acreage in the first quintile) use any of these four technologies. This use could be due to scale benefits (i.e., the returns to technology adoption could be greater on larger farms than on smaller farms).

- **DA technology adopters use data, acquire crop management recommendations, and employ technical/consultant services at higher rates than DA technology nonadopters:** DA technology adopters are more likely than nonadopters to download public data for use in decision-making, though overall adoption remains uncommon. By contrast, farmers more frequently obtain crop management recommendations based on technologies that collect data in their fields. And while technical/consultant services are hired on a small fraction of surveyed acres, such services tend to be sought somewhat more by DA technology adopters.

- **Farmers are likely to use precision agriculture technologies for a variety of reasons**: As technological capabilities continue to evolve, so have farmers' rationales for their use. For example, corn and winter wheat farmers tend to rely on yield monitors to track crop moisture content. By contrast, yield monitors are primarily used to help determine chemical input use in cotton, soybeans, and sorghum production. Many precision agriculture technologies are used in combination with other precision agriculture technologies.

How Was the Study Conducted?

The study uses data from the Agricultural Resource Management Survey (ARMS), administered jointly by the USDA, Economic Research Service (ERS) and the USDA, National Agricultural Statistics Service (NASS). The authors analyze precision agriculture adoption, emphasizing the most recent commodity-specific surveys: rice (2013), corn (2016), winter wheat (2017), soybeans (2018), cotton (2019), and sorghum (2019). To illustrate the continuity of historical trends, we also use data from earlier ARMS surveys dating to 1996. Data from the 2013 and 2019 ARMS Cost and Returns Report are also used to track national adoption of global navigation satellite systems (GNSS). The focus is on the key precision agriculture technologies mentioned above. The study also explores several drivers of DA adoption using ARMS data and information via the RCA (Soil and Water Conservation Act of 1977) Data Viewer from USDA's Natural Resources Conservation Service. Additionally, the study incorporates evidence from the literature and makes comparisons with other U.S. farm sector trends.

Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms

Introduction

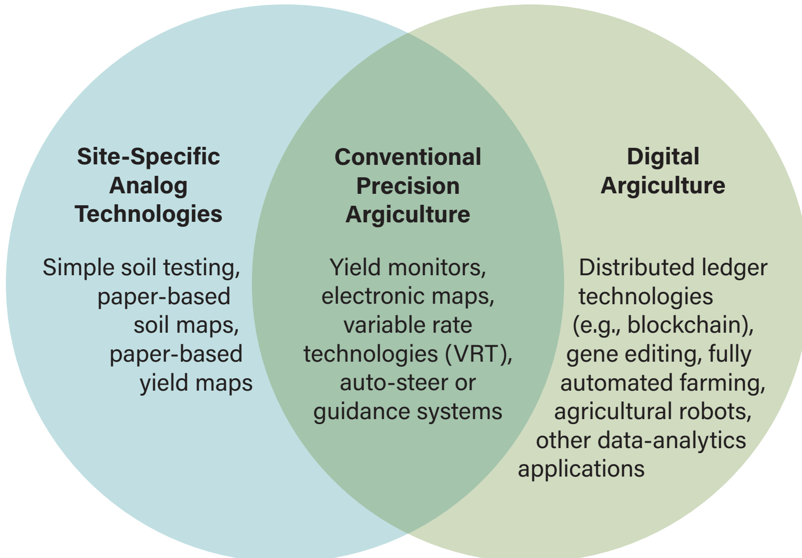
In recent decades, U.S. row crop production has faced significant pressures from climate change, pesticide resistance, an aging farmer population, labor shortages, shifts in the geography of international commodity trade, and dietary transitions, among other challenges (Castillo et al., 2021; Whitt et al., 2021). No single technology or set of technologies can fully address these challenges. Adjustments will entail, among many other things: new seed varieties and combinations of more sustainable production practices (e.g., conservation tillage, cover crops), new pesticide products and methods of pest management, and potential changes to incentive structures and the mix of labor and capital used on farmers' fields to partly resolve excess labor demand. In response, digitalization—among the farthest-reaching technological transformations of the economy in this era—has become a focal point for agricultural policymakers seeking a holistic, multipronged solution to these challenges (DeBoe and Jouanjean, 2019; Food and Agriculture Organization of the United Nations (FAO), 2020; Basso and Antle, 2020; McFadden et al., 2022b).[1]

Digital agriculture (DA) refers to the diffusion of information technologies (e.g., the internet and Internet of Things (IoT), mobile devices, and predictive analytics) to enhance the collection, exchange, combination, analysis, and access of digital content within the agricultural sector. The agricultural digitalization process entails greater use of precision agriculture technologies; the promotion of data-sharing between farmers, data aggregators, and input companies; and reliance on data-driven decision making for day-to-day management of farm operations. This latter form of decision making includes choices that operators make about which on-farm tasks to automate (e.g., Acemoglu and Restrepo, 2019). Currently, DA encompasses many established technologies generally referred to as precision agriculture (e.g., electronic maps, VRT, guidance systems) whose adoption has been tracked nationally by USDA for many years. However, several digital technologies (e.g., distributed ledger technologies, gene-edited crops and livestock, and cellular agriculture) have emerged more recently and are not universally considered to be precision agriculture (PA) by conventional standards, in part because they are aspatial (see figure 1). Because of this relatively recent emergence, farmers' uptake of these technologies has yet to be tracked on a consistent and nationally representative basis (Graff et al., 2021).[2]

[1] For context, precision farming involving digitalized tools has been termed in some instances as "Agriculture 4.0" (DeBoe and Jouanjean, 2019).

[2] The same is generally true regarding industry data. Nationally representative surveys of large equipment manufacturers do not typically inquire about sales of precision equipment. However, the well-known CropLife-Purdue University Precision Agriculture Dealership Survey is an annual detailed survey of dealers about precision technologies used in their business and products/services sold to farmers since 1997 (Erickson et al., 2017; Erickson et al., 2020). Moreover, a recent influx of venture capital funding has resulted in the creation of many new technology start-ups in the digital agriculture sector (Graff et al., 2021).

Figure 1
Relationship between site-specific management, precision agriculture (PA), and digital agriculture (DA)



Note: Diagram is meant to be illustrative rather than comprehensive.

Source: USDA, Economic Research Service illustration.

The ongoing digitalization of U.S. agriculture presents considerable opportunity for improvements in farmers' productivity, environmental footprint, and risk management. For example, to the extent that variable rate technologies (VRT) lead to lower rates of fertilizer applications or more appropriate timing and location of applications, nutrient leaching and run-off concerns could be lessened. There are similar implications associated with variable-rate pesticide applications (e.g., reduced off-target movement and the possibility of delaying inevitable pesticide resistance) and irrigation applications (e.g., freshwater conservation). The use of automated guidance or controlled traffic farming systems simplifies farmers' in-cab time and can potentially reduce fuel consumption, greenhouse gas emissions, and soil compaction. Mapping technologies are often used to identify field drainage problems that, when addressed, can prevent overwatering of crops (e.g., Saavoss et al., 2021).

In this report, we detail recent trends in adoption rates of precision technologies on certain U.S. row crop fields—first providing an overview and describing the broad types of tools that, collectively, comprise key features of the digital agriculture architecture. We also analyze differences in certain characteristics between fields on which DA is adopted and not adopted. In turn, we identify and discuss key drivers of adoption, with an emphasis on important determinants that have been underexplored to date—including technology prices (replacement costs, fees, and premiums), USDA programs, and labor-saving benefits. However, we do not review adoption trends in specialty crops (i.e., fruits, vegetables, tree nuts, and other horticultural crops) or livestock, as there are no national adoption data for these sectors.

We find that yield map adoption has steadily increased since the late 1990s and early 2000s, in contrast to Global Navigation Satellite System (GNSS)-based soil maps, which appear to have flattened—with relatively low adoption rates—for several crops starting between 2009 and 2011. Currently, the majority of acreages for each of six major row crops (corn, soybeans, winter wheat, cotton, rice, and sorghum) are managed with guidance systems, up from minimal adoption in the early 2000s. Despite recent upturns in VRT adoption, its use remains limited, though VRT use is much more common than drones and other aerial-based technologies. Substantial heterogeneity exists across technologies and crops regarding drivers of adoption, which we discuss at length below. Beyond well-documented determinants relating to market structure (farm size, costs, and expected productivity impacts), we find important roles played by human resources (e.g., expected labor-saving benefits, skills requirements) and natural resources (e.g., soil variability, field topography, and conservation program incentives).

This report updates two earlier USDA, Economic Research Service (ERS) studies, Schimmelpfennig and Ebel (2011) and Schimmelpfennig (2016), which examined precision agriculture adoption trends. We extend their analyses through the most recent 4 years for which data are available, 2016–19. Unlike Schimmelpfennig (2016), we do not formally analyze the role of DA technologies for improving farm profitability. Although digitalization of U.S. row crop farming has deepened in the intervening years, as reflected in this report's updated adoption statistics, we do not expect the underlying economics of production to have changed in a way that would produce estimates of profitability effects that would differ markedly from those reported in Schimmelpfennig (2016). We also do not formally investigate digitally-facilitated changes in the environmental footprint of U.S. agriculture.

Data Sources

Multiple years of the Agricultural Resource Management Survey (ARMS) are the main data sources for this report. ARMS is administered jointly by USDA's Economic Research Service (ERS) and the USDA, National Agricultural Statistics Service (NASS) and is an annual survey of farms' production practices (i.e., equipment adoption, field operations, chemical use, crop rotations, tillage, and seed choices), farm financial characteristics, and farm household demographics (see box, "Overview of the USDA Agricultural Resource Management Survey").

We use field-level production data from ARMS Phase II for all survey years between 1996 and 2019, except for 2008 and 2014 (see table in box, "Overview of the USDA Agricultural Resource Management Survey"). Our sample represents virtually all U.S. acreage planted to the crop in the particular-survey year for which data are available. We supplement the ARMS data with information about acreages enrolled in USDA's Conservation Stewardship Program (CSP), available through the National Planning and Agreements Database (NPAD) from USDA's Natural Resources Conservation Service (NRCS).

Overview of the USDA Agricultural Resource Management Survey (ARMS)

The USDA's Agricultural Resource Management Survey (ARMS) is the main source of data used in this report. An annual survey of U.S. farms, ARMS is USDA's primary source of information about the financial conditions, production practices, and the economic well-being of the agricultural sector. ARMS is jointly administered by both USDA, Economic Research Service and USDA, National Agricultural Statistics Service.

ARMS is a multiframe, stratified, and probability-weighted survey conducted in three phases:

- Phase I is undertaken in the summer of the reference year and screens farms for survey eligibility.
- Phase II takes place during the fall of the reference year and collects field-level information on production practices, natural resource use, pesticide and fertilizer applications, and other input use for a target crop.
- Phase III is conducted in the spring after the reference year and collects farm-level information about finances, operator and household characteristics, and demographics. Farms surveyed for a target crop in Phase II are also asked to complete the Phase III survey, and these respondents form a subset of the Phase III sample. Phase III samples all types (e.g., row crops, livestock, specialty crops) and all sizes (e.g., very small to very large) of farms across the contiguous 48 States.

continued on next page ►

continued from previous page ►

Data for this report are primarily from Phase II of ARMS. ARMS surveys the same target crop every 4 to 6 years. Each of the several major field crops (e.g., corn, soybeans, wheat, cotton, sorghum, rice) are surveyed on a rotating basis every 4 to 6 years, though not all major row crops are surveyed. Each of the surveyed fields (one per farm in the sample) is randomly selected. Enumerators conduct the survey in person, which contributes to data accuracy and fewer missing responses.

The trends depicted and discussed in this report rely on responses from surveys conducted in reference years 1996–2007, 2009–13, and 2015–19. In 2008, Phase II of the survey was not administered to any farms. Similarly, in 2014, ARMS focused on tenure, ownership, and transition of agricultural land, and thus no field-level adoption data were collected. Since major crops are surveyed on a rotating basis, adoption data are not available in all years. This report accounts for the statistically complex survey design to ensure that findings are statistically representative of U.S. corn fields and acreage.

Availability of Precision Agriculture Adoption Data from ARMS Phase II, 1996–2019

Year	Corn	Soybeans	Winter wheat	Cotton	Sorghum	Rice
1996		■				
1997	■	■				
1998	■	■	■			
1999	■	■				
2000	■	■	■	■		
2001	■					
2002		■				
2003				■	■	
2004			■			
2005	■					
2006		■				■
2007				■		
2008						
2009			■			
2010	■					
2011					■	
2012		■				
2013						■
2014						
2015				■		
2016	■					
2017			■			
2018		■				
2019				■	■	

Note: ARMS = Agricultural Resource Management Survey. Shaded cells indicate that the particular crop was surveyed in the indicated year. Since 2001, the ARMS methodology has targeted one or more crops on a rotating basis, which implies that each of the targeted commodities are not surveyed every year.

Source: USDA, Economic Research Service and National Agricultural Statistics Service (NASS), Agricultural Resource Management Survey (ARMS), Years 1996–2007, 2009–13, 2015–19.

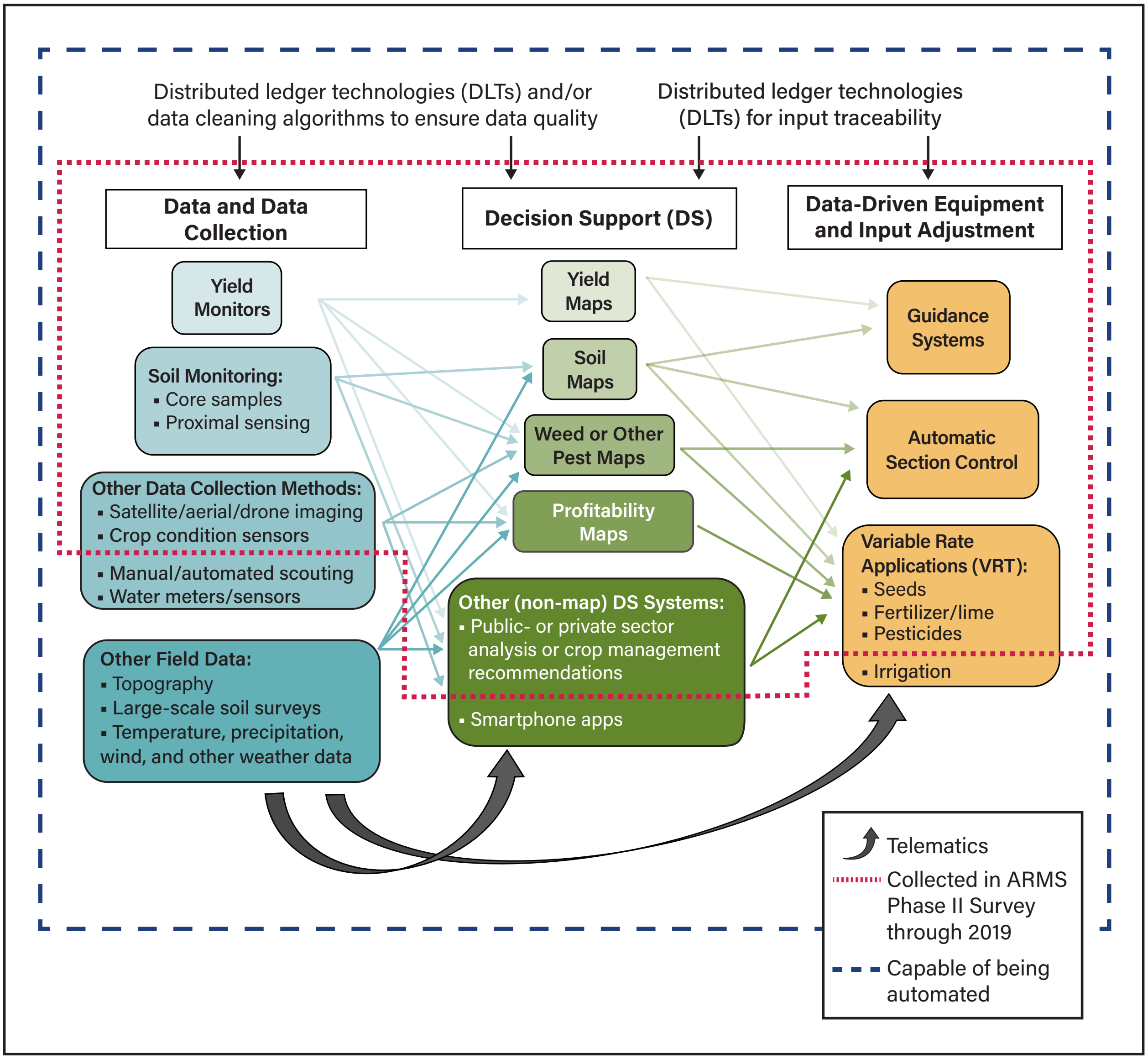
What Are the Components of Digital Agriculture (DA)?

Many of the major components of digital agriculture can be decomposed into three features: (1) data and data collection systems, (2) decision support (DS) tools, and (3) data-driven equipment and input adjustments[3] (figure 2). Examples under the first category include data from yield and soil monitoring equipment, various sensors, and imagery from drones, aircraft or satellites. DS tools include (electronic) maps or other visualizations of georeferenced data, in addition to smartphone apps and other sources of analysis with management recommendations. Technologies falling under the third category are largely guidance systems, automated section control, and variable rate applicators.

USDA adoption data are available for many of the technologies underlying digital agriculture (see items appearing within red dashed line in figure 2), though not all. For example, adoption of distributed ledger technologies (e.g., blockchain), which can be used to ensure data quality or assist with input traceability, is not tracked. Adoption information is also not currently available for telematics (described below), smartphone applications (apps), or variable rate irrigation among others. A number of industry reports suggest that smartphone use is widespread across the U.S. farming sector (e.g., United Soybean Board, 2019), while variable rate irrigation remains limited (Lamm et al., 2021) and the subject of much ongoing research and development (e.g., Saavoss et al., 2021).

[3] Arrows in figure 2 indicate the flow of hardware, software, or information as inputs. For example, the four arrows pointing away from the “Yield monitors” box indicate that yield monitor data are used to construct yield maps, weed or other pest maps, profitability maps, and other non-map decision-support systems. Moreover, the blue dashed box encapsulating the entirety of the features in figure 2 is a conceptual representation of the idea that virtually all features of U.S. row crop farming are, or can be, automatable.

Fi gure 2
Key component technologies of digital agriculture (DA)



Note: Arrows indicate the flow of hardware, software, or information—as inputs—to decision support (DS) technologies and/or data-driven equipment or input adjustments. Although gene editing and cellular agriculture are components of digital agriculture, they are not depicted here as they are beyond the scope of the report. The dashed line indicating "capable of being automated" is designed to suggest that virtually all components of digitally-enabled production systems can be automated (i.e., autonomous machinery is not a single-component technology).

Source: USDA, Economic Research Service illustration.

The current status of U.S. agricultural digitalization can only be fully explored and discussed by first reviewing the underlying technologies and associated data use. In order to do so, basic descriptions of each of the major technologies or systems are required (see table 1). Additional technical details are provided in the appendix, "Overview of DA Component Technologies."

Table 1
Key component technologies of digital agriculture, 1996–2019

Technology	Description	Category	Year commercialized
Yield monitor	In-cab device that displays crop yields (e.g., bushels/acre)—and how those yields change over small areas.	Data collection	1993
Precision soil sampling	Soil core samples are taken from grids or other areas, typically less than 10 acres in area. Samples are analyzed in laboratories to determine the soil's physical and/or chemical properties.	Data collection	1993
Yield maps, soil maps	Yield maps are physical maps that visually represent crop yields and variation in yields within and across fields. Likewise, soil maps display physical and/or chemical attributes of soils.	Decision support	Approximately 1993–94
Variable rate technologies	Equipment that provides custom applications of seed, lime, fertilizer, and/or pesticides at rates that can change over small distances.	Data-driven equipment	1995
Guidance systems	Equipment that reduces field overlaps or skips by either (1) instructing the operator to steer within predefined boundaries (e.g., lightbars) or (2) fully automates nearly all steering operations.	Data-driven equipment	Lightbars: mid-1990s; full automation: late 1990s
Drones, aircraft, or satellite imagery	These kinds of imagery (with various uses) are remotely-sensed data collected from satellite, crewed aircraft (typically small propeller planes), or small unmanned aerial vehicles (e.g., fixed wing or rotorcraft drones).	Data, data collection	Landsat satellite imagery: 1970s; commercial drones: mid-2000s
Automated section control	Type of variable rate technology that automatically shuts off a portion of the equipment (e.g., boom section, nozzle on sprayer, or row on planter) when the portion is in a part of the field that does not require input application.	Data-driven equipment	2003
Controlled traffic farming	A farming practice that limits exposure of the soil's surface to farm equipment's tires or tracks (through the use of tramlines), so that the equipment returns to the same tracks for each trip, for as many field operations as possible.	Data-driven equipment	Late 1970s to early 1980s
Telematics	The wireless transfer of data between farm equipment, connected devices, and/or the cloud via cellular systems or local area networks (e.g., Bluetooth).	Decision support	2002

Note: This table emphasizes the key technologies discussed in this report. Nationally representative data are not generally available regarding farmers' use of other technologies frequently considered to be part of digital agriculture (e.g., distributed ledger technologies, gene-edited crops, highly specialized and mobile agricultural robots). Yield-monitoring technologies date to the 1960s, though the advent of GPS for civilian purposes has rendered yield monitoring much more available. Similarly, grid soil sampling also predates the advent of civilian-use GPS.

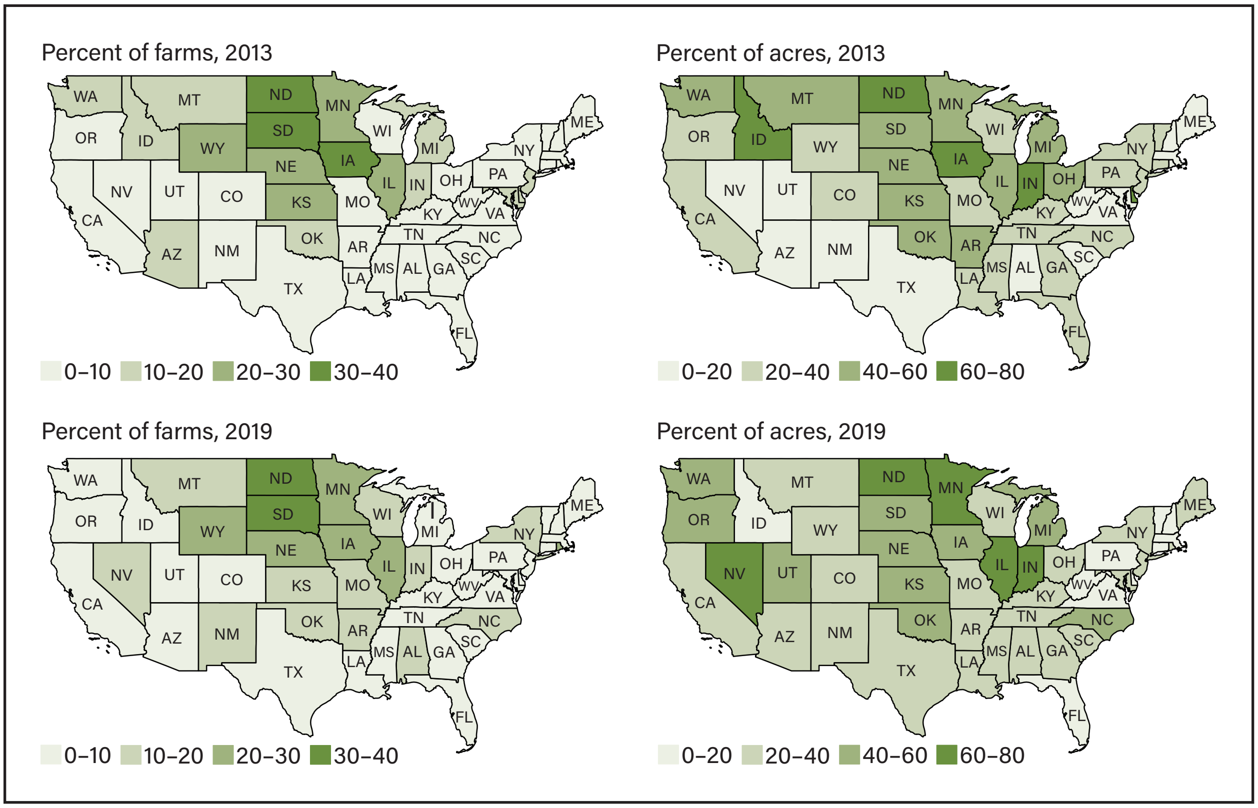
Source: USDA, Economic Research Service.

Because of their significant use in row crop production, this report mainly focuses on yield monitors, precision soil sampling, yield and soil maps, VRT, guidance systems, aerial imagery (from drones, aircraft, or satellites), automated section control, controlled traffic farming, and telematics. As discussed above, these technologies fall mainly within the realms of data and data collection, decision support, or data-driven equipment and input adjustment technologies. Underlying the widespread use of nearly all these technologies, however, was the advent of the U.S. Department of Defense's Global Positioning System (GPS) in 1978, which was made "selectively available" to civilians starting in 1983. Geospatial coordinates from GNSS systems (such as GPS) make it possible for technology providers to create maps, enable the automated controllers mounted within VRT machinery, and facilitate modern guidance systems. In short, satellite navigation systems like GPS are a fundamental technology that supports site-specific management.

In 2013 and 2019, roughly 12 percent of all U.S. farms—representing 37 percent and 40 percent, respectively, of total farm/ranch acreage—made use of GPS for on-farm production activities (figure 3).[4] At the general farm level, adoption of specific GPS applications (e.g., VRT, guidance, mapping) are unknown, but considerable variability exists across States. In both years, well over half of farm/ranch acres were managed with GPS in the Corn Belt (Illinois, Indiana, Iowa, Kansas, Minnesota, North Dakota, South Dakota), while adoption was less than 10 percent of farm/ranch acres for certain Eastern States (Massachusetts, New Hampshire, and West Virginia). These differences reflect geographic variation in the quality of satellite signal reception, the types of crops that are grown, and the expected net returns to GNSS applications.

Figure 3

Percent of total farms and total farm/ranch acres using GPS for on-farm production activities, 2013 and 2019



Note: The top panels depict the percent of each State's total farms and total farm/ranchland, respectively, in 2013, with operators who indicated they used GPS for on-farm production activities. Similarly, the bottom panel depicts these percentages for year 2019. Data are not available for Alaska and Hawaii.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2013 and 2019 Agricultural Resource Management Survey (ARMS).

Beyond the above-mentioned broad types of technologies, however, there are two other related concepts: emerging digital technologies and digital components used within a system. Emerging technologies available in other nonagricultural sectors have been implemented within the U.S. farm sector. Automation of processes is not new to agriculture; as noted above, automated guidance and automated section control have become quickly adopted technologies within the farmgate. In the last decade, automation of routine farm

[4] The disparity between percentages of farms and percentages of acres reflects the well-known facts that: (1) the farm size distribution is prominently left skewed (i.e., there are many more small farms than large farms), and (2) larger farms adopt advanced technologies at higher rates than small farms (MacDonald et al., 2013).

data tasks has been undertaken via telematics for data transfer (Whitacre et al., 2014), algorithms for cleaning and analyzing yield monitor data, and distributed ledger technology (i.e., blockchain, which allows for data quality assurance and monitoring chain of custody) (Griffin et al., 2022).

Artificial intelligence (AI), machine learning, and associated computer innovations have been touted to enable greater productivity across agricultural sectors, although little evidence exists to date because they have not yet been deployed at scale. Algorithms have replaced human intervention for repeatable tasks involving certain kinds of decision making (e.g., Acemoglu and Restrepo, 2019).

Moreover, component technologies have been integrated into digital systems for greater use within the farm-gate. Underlying such integration has been the resurgence of on-farm experimentation managed by farm operators, where each component technology empowers the farm operator to better implement, harvest, and analyze the experiment if that component is used in a holistic system (Lacoste et al., 2022). In the past, ARMS questionnaires asked about how farm operators used GNSS-enabled yield monitors for on-farm activities, reporting that use in experimentation often was higher than that of use related to other landowner decisions (e.g., negotiating new crop leases, documenting yields for financial purposes, dividing crop production among those receiving a share of the crop). As early as 2002, soybean farmers listed conducting on-farm experiments as the third-highest use of yield monitor data. The question regarding usage of yield monitor data included a response category of "conduct in-field experiments (e.g., compare fertilizer applications, seed varieties, herbicides, pesticides, etc.)" from 2002 to 2011. In 2011, the most recent year for which data are available, nearly 25 percent of acreage planted to sorghum or barley was harvested with a combine equipped with a yield monitor to collect data from a deliberate in-field experiment.

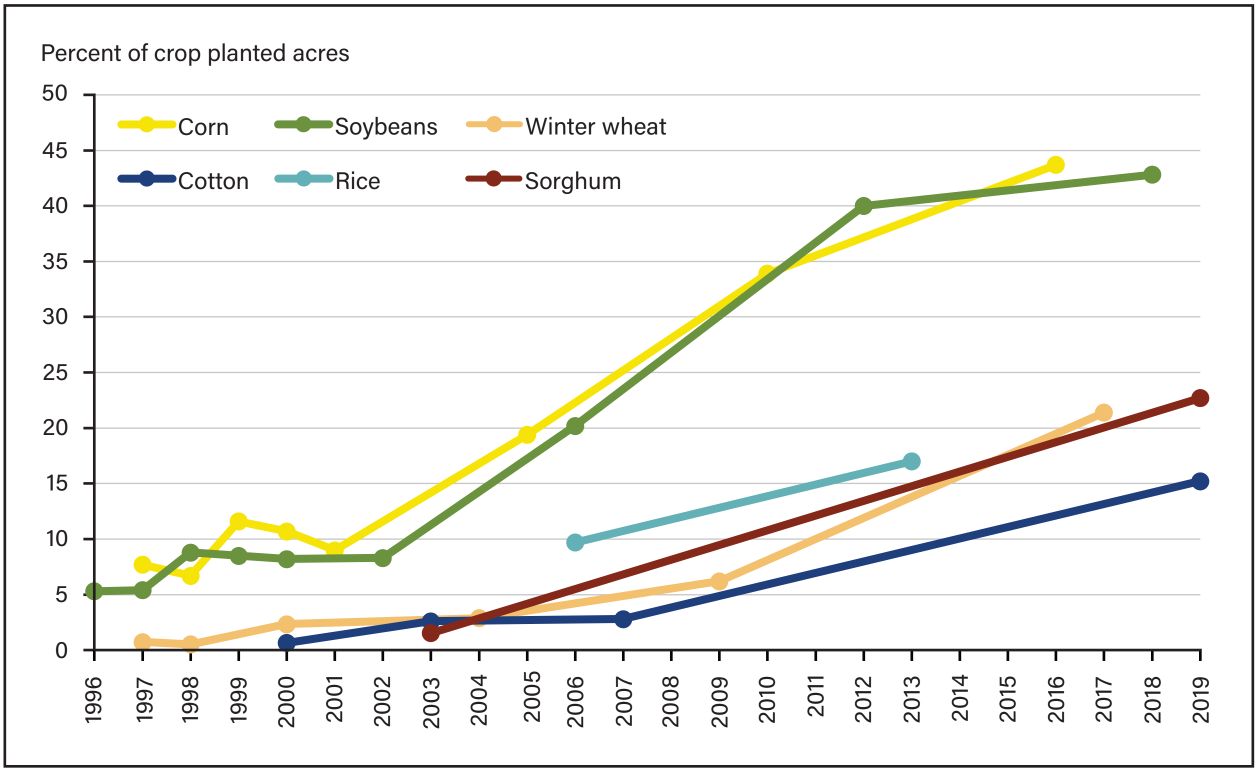
How Has Adoption of DA Component Technologies Changed in Recent Years?

Adoption of precision technologies related to digital agriculture has increased considerably since the mid-1990s. Below, we review trends in the adoption of fundamental precision agriculture technologies: yield maps, yield monitors, soil maps, variable rate technologies (VRT), drones, aircraft or satellites, and auto-steer and guidance systems, in addition to technology combinations.

Yield Maps

Yield maps have been available since the early 1990s and are primarily used by agricultural producers to quantify and characterize within-field production variability. Mapping of average spatial and temporal patterns in yields is valuable to producers because they provide information critical to making informed and reliable management decisions. The maps are typically used to analyze factors affecting field-yield variation and to prescribe variable-rate applications for other factor inputs, such as fertilizers and pesticides. Yield maps are generated using yield monitors, which were once usually mounted on combine harvesters or other forms of auto-guidance systems but are now standard on new equipment (Schimmelpfennig and Ebel, 2016). Information from Phase II of the Agricultural Resource Management Survey (ARMS) for several years across various row crops (including corn, soybeans, winter wheat, cotton, sorghum, and rice) indicates considerable (albeit varying) adoption rates by row crop. Adoption rates increased from 5.3 percent in 1996 to 43.8 percent in 2018 across soybean-planted acres; adoption rates across corn-planted acres stood at 43.7 percent in 2016, up from a low of 7.7 percent in 1997 (figure 4).

Figure 4
U.S. farmers' increasing yield map adoption, 1996–2019



Note: Starting in 2015, the adoption of a yield map is considered to be the use of yield monitor data that were/will be used to create a map.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 1996–2007, 2009–13, 2015–19.

Adoption rates across other row crops have ranged from 1.5 percent for sorghum in 2003 to 22.7 percent in 2019; 0.7 percent in 1997 to 21.4 percent in 2017 for winter wheat; and from 0.7 percent in 2000 for cotton to 15.2 percent in 2019. It is important to note that consistent spatial and temporal patterns in yields may be confounded by factors ranging from weather variability and changing soil quality to pest pressure and any other common factors that could prevail during the cropping season (Basso et al., 2012). A long yield history is essential in order to avoid misinterpreting information generated from yield maps. A solution to this potential misinterpretation is the use of high-resolution yield monitors.

Yield Monitors

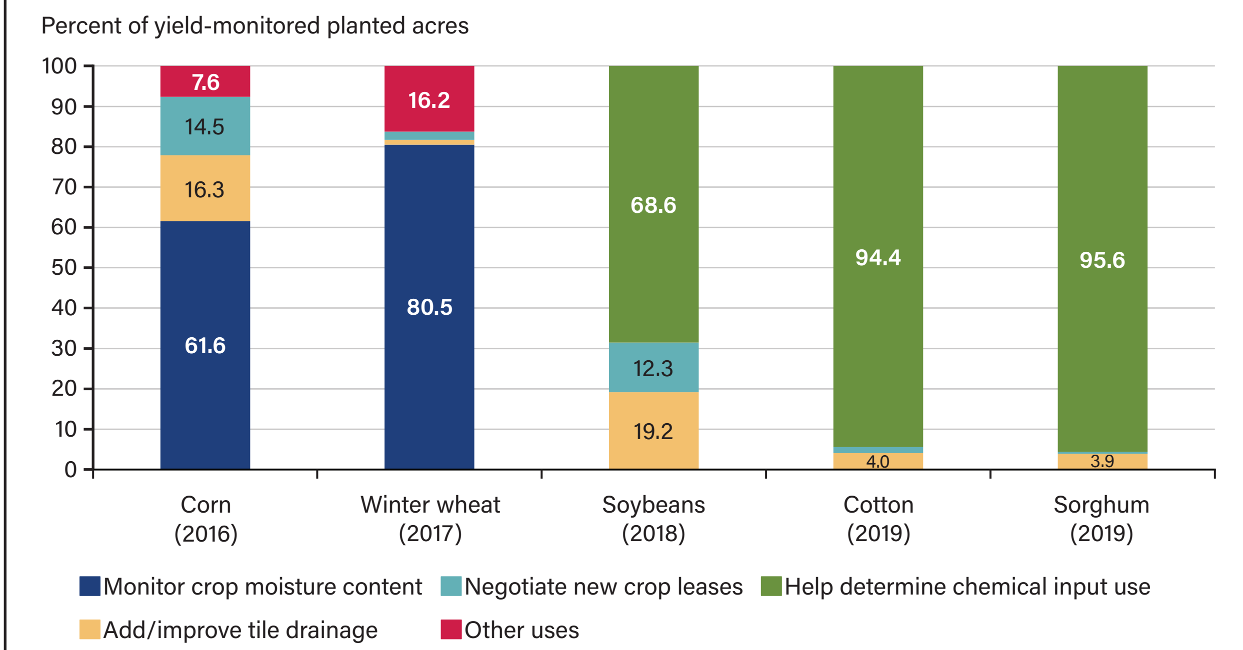
Yield monitors consist of three components: a mass flow sensor that monitors grain flow in order to establish grain yield measurement; a moisture sensor that captures moisture content in grain in order to aid in storage and drying of the harvest; and a differential global positioning system (DGPS) receiver that records and geo-references the location (i.e., associates physical locations with geographic coordinates).[5] When properly calibrated, yield monitors are capable of generating accurate information that can be used to aid current and future decision making.

Yield monitoring can also be used to identify where chemical inputs are most efficient, enabling the design of specific crop fertilization programs. Across U.S. planted acreage, farmers have relied on yield monitors for various reasons. Recent data indicate that these technologies were used to monitor crop moisture content

[5] Moisture-sensing is essential to correcting yield data in order to accurately determine the marketable weight of grain.

on 61.6 percent of corn-planted acres in 2016 and 80.5 percent of winter wheat acres in 2017 (figure 5). Meanwhile, of the farms adopting yield monitors—95.6 percent, 94.4 percent, and 68.6 percent of sorghum (2019), cotton (2019), and soybean (2018) planted acres, respectively—were managed with yield monitors to help determine chemical input use. Farmers can also use information generated by yield monitors to add or improve tile drainage and/or other water-related technologies (e.g., irrigation equipment), among several other uses.

Figure 5
Farmers' use of yield monitor data: Substantial variation by crop and year



Note: In 2016 and 2017, the underlying survey question from which the data were taken had four answer choices, as depicted above. In 2018 and 2019, wording to the survey question was changed so that respondents could choose from one or more of the three answer choices depicted above.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 2016–19.

Soil Maps

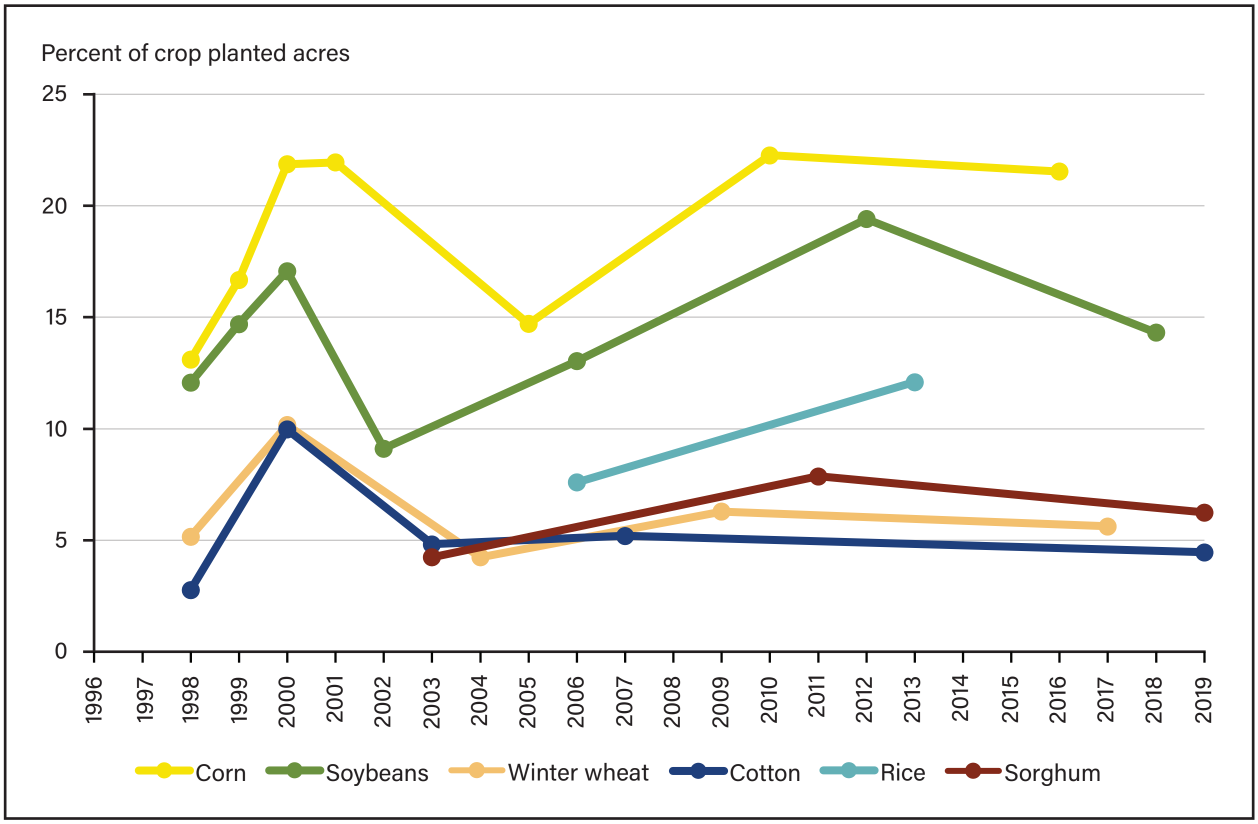
Soil mapping is used to identify soils and their properties. There are generally two levels of soil maps for land-use management. The first level comprises an inventory of soil properties or conditions of the soil at the time of mapping, and a second level comprises interpretation, which synthesizes soil properties and site context (Miller, 2017). In agricultural land management, soil mapping is used as a decision tool to determine the suitability of specific soils to particular crops, as well as their drainage capability, among other uses.

A relatively new tool is digital soil mapping, a feature that entails the creation of geographically-referenced soil databases that facilitate the rapid visualization and quantification of landscape patterns at multiple spatial scales (McBratney et al., 2003). Digital soil mapping is largely enabled by a highly comprehensive, interactive database of detailed soil maps maintained by the USDA, Natural Resources Conservation Service (NRCS). These maps can also track soil characteristics that gradually vary over time. However, such maps do not reveal certain highly dynamic, localized, and history-dependent soil characteristics like compaction, and outdated maps will not indicate up-to-date nutrient needs; both characteristics tend to substantially influence crop performance in any given year.

Information from ARMS reveals that the adoption of soil maps has lagged behind other DA components, with adoption rates remaining consistently below 25 percent of planted acreage across surveyed crops. The proportion of land managed with soil maps includes only 21.5 percent of corn-planted acres in 2016, 14.3 percent of soybean-planted acres in 2018, 6.2 percent of sorghum-planted acres in 2019, and 5.6 percent of winter wheat-planted acres in 2017 (figure 6). These adoption rates are consistent with a general trend for row crop farmers in the Central United States to only sample their soils at discrete intervals (usually 3 to 4 years).

Figure 6

Soil map adoption, 1996–2019: Rates increased slightly or flattened



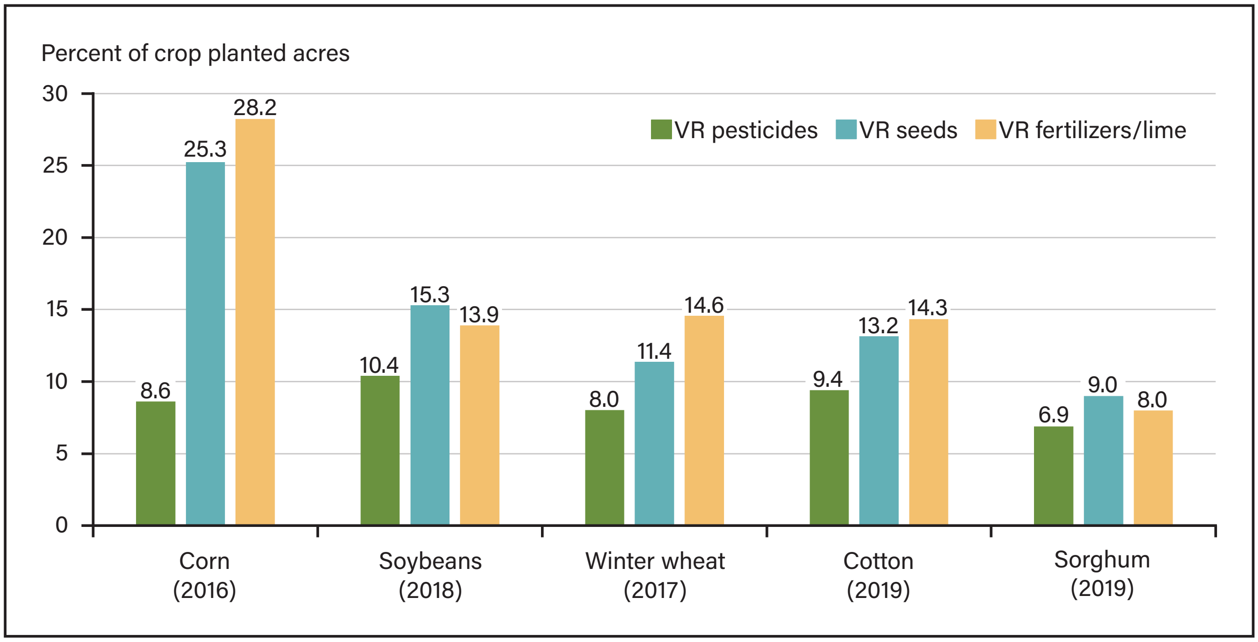
Note: Starting in 2015, the adoption of a soil map is considered to be the use of data from: (1) soil tests on core samples (performed on-farm or sent out to a laboratory), and/or (2) soil sensor tests that were/will be used to create a map.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 1998–2007, 2009–13, 2015–19.

Variable Rate Technologies (VRT) and Automated Section Control (ASC)

Variable rate technologies (VRT) are currently used by farmers to perform various on-farm tasks, including seeding and applications of fertilizer, lime, and pesticides (figure 7). VRT enables greater control of important variable inputs, possibly leading to more efficient applications without a loss of yields and potentially lowering total production costs (Schimmelpfennig and Ebel, 2016). VRT can also help to reduce fertilizer leaching or run-off through adjustment of application rates, thus potentially contributing to more sustainable commodity production (Basso and Antle, 2020).

Figure 7
Percentages of variable rate technology (VRT) used on U.S. crop-planted acres



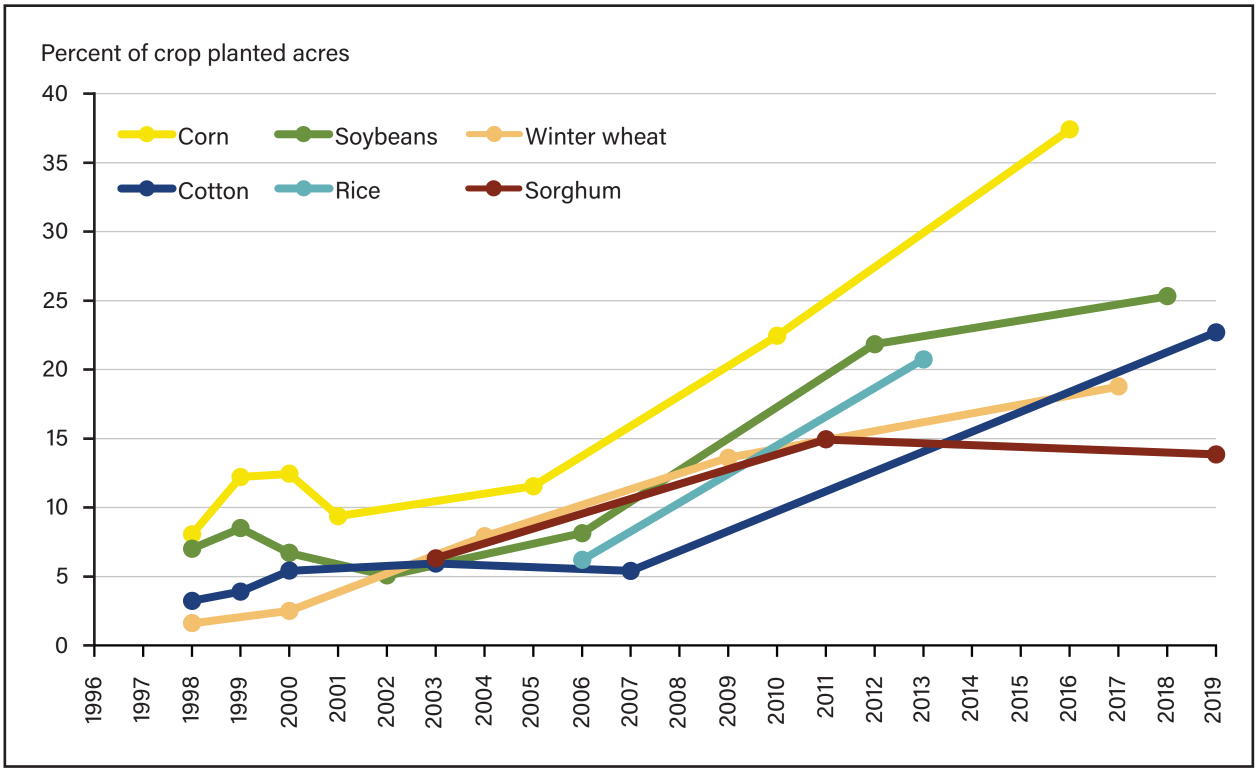
Note: VRT is commonly used for lime applications. However, due to survey question wording, variable rate (VR) fertilizer applications cannot be distinguished from VR lime applications. Data are not available for VR irrigation applications.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 2016–19.

Notwithstanding the prospects of lower costs associated with VRT, its use on U.S. farms is far from universal (Bullock et al., 2009; Schimmelpfennig and Ebel, 2016; Lowenberg-DeBoer and Erickson, 2019). More specifically, VRT adoption follows a common pattern: Higher adoption by large farms and low uptake among smaller farms indicates the potential for scale benefits.[6] According to the ARMS data, VRT adoption rates stood at 37.4 percent on corn-planted acres and 25.3 percent for soybean-planted acres in 2016 and 2018, respectively (figure 8). VRT adoption rates across other row crops ranged from 18.8 percent of winter wheat-planted acres in 2017, 13.9 percent for sorghum in 2019, and 22.7 percent for cotton in 2019.

[6] Returns to technology adoption may be greater for larger farms, as adjustment costs can be spread over a larger amount of goods produced.

Figure 8
Variable rate technology (VRT) use: Substantial expansion from 1996–2019



Note: Any VRT adoption is considered to be the use of a variable rate applicator for seeding, fertilizer/lime applications, or pesticide applications. The use of VR applicators for irrigation are not considered, as no data are available.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 1998–2007, 2009–13, 2015–19.

Beginning in 2019, the ARMS started inquiring about farmers' use of automated section control (ASC) technologies such as auto sprayer boom controls and automatic row shut offs for planters. ASC is similar to VRT in that it can automatically turn "on" parts of the equipment that are directly over areas that need seeds, fertilizer, or pesticides and "off" when directly over parts of the field that already received inputs or do not need applications. In 2019, ASC was used on 41 percent of U.S. cotton acres, 45 percent of sorghum acres, and 48 percent of barley acres.

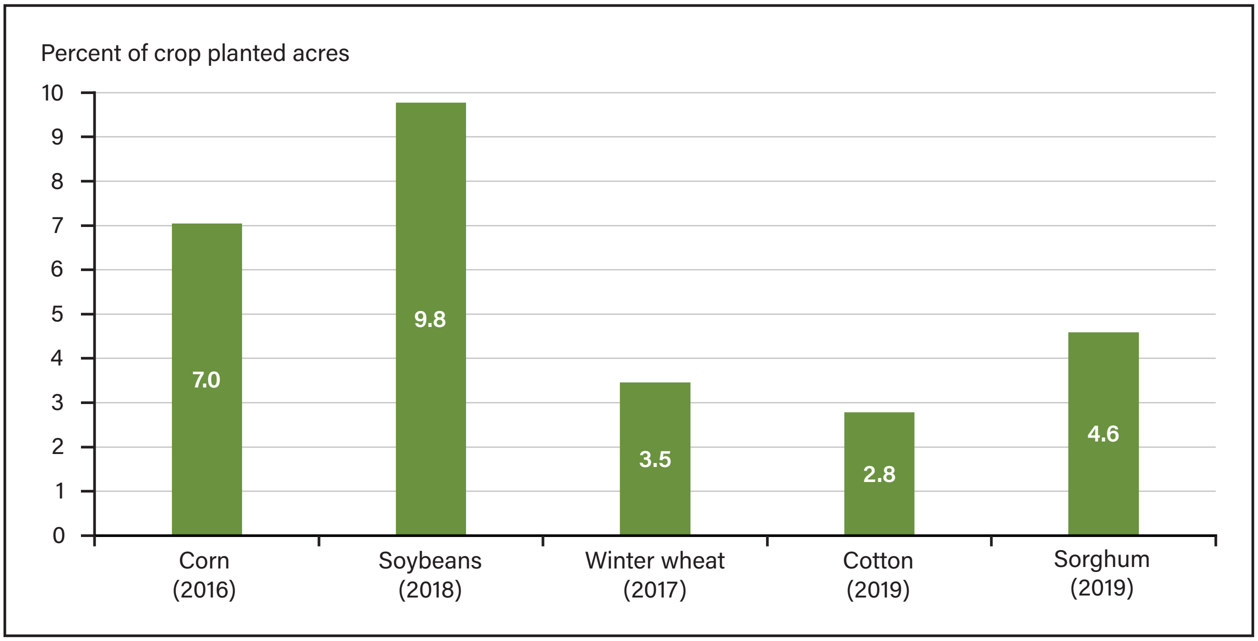
Drones, Aircraft, or Satellites

While aircraft have been used on many farming operations for decades, unmanned aerial vehicles (UAVs) or drones are a newer feature of digital agriculture that—when equipped with satellite tracking or GNSS technology—can help to optimize farmland management. Collectively, these tools are used mostly for: crop mapping, livestock monitoring, land surveying, crop spraying, and crop dusting. When equipped with GNSS technology, UAVs can geo-reference vast stretches of farmland, which can aid farmers' decision making (e.g., helping to identify land features or vegetation patterns that are more easily visible from above).

According to the most recent data, adoption of these tools remains limited (figure 9). Across the various row crops surveyed, adoption rates ranged from 7.0 percent for corn in 2016 to 9.8 percent for soybeans in 2018. Meanwhile, the adoption rate on winter wheat-planted acreage in 2017 was 3.5 percent, with comparable adoption in 2019 on cotton acres (2.8 percent) and sorghum (4.6 percent).[7]

[7] The commodity-specific ARMS questionnaires in these years do not elicit information from farmers about barriers to adoption. Nonetheless, low adoption for aircraft may be driven (in part) by their technological complexity, as well as substantial expense in their use. These barriers may also underly the low adoption rates for drones, in addition to perceptions of a limited number of uses on the farm.

Figure 9
Drone, aircraft, and satellite imagery use remains low



Note: Due to survey question wording, the use of drones, aircraft, and satellites cannot be separately distinguished, and adoption estimates are only available for these three technologies in aggregate.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 2016–19.

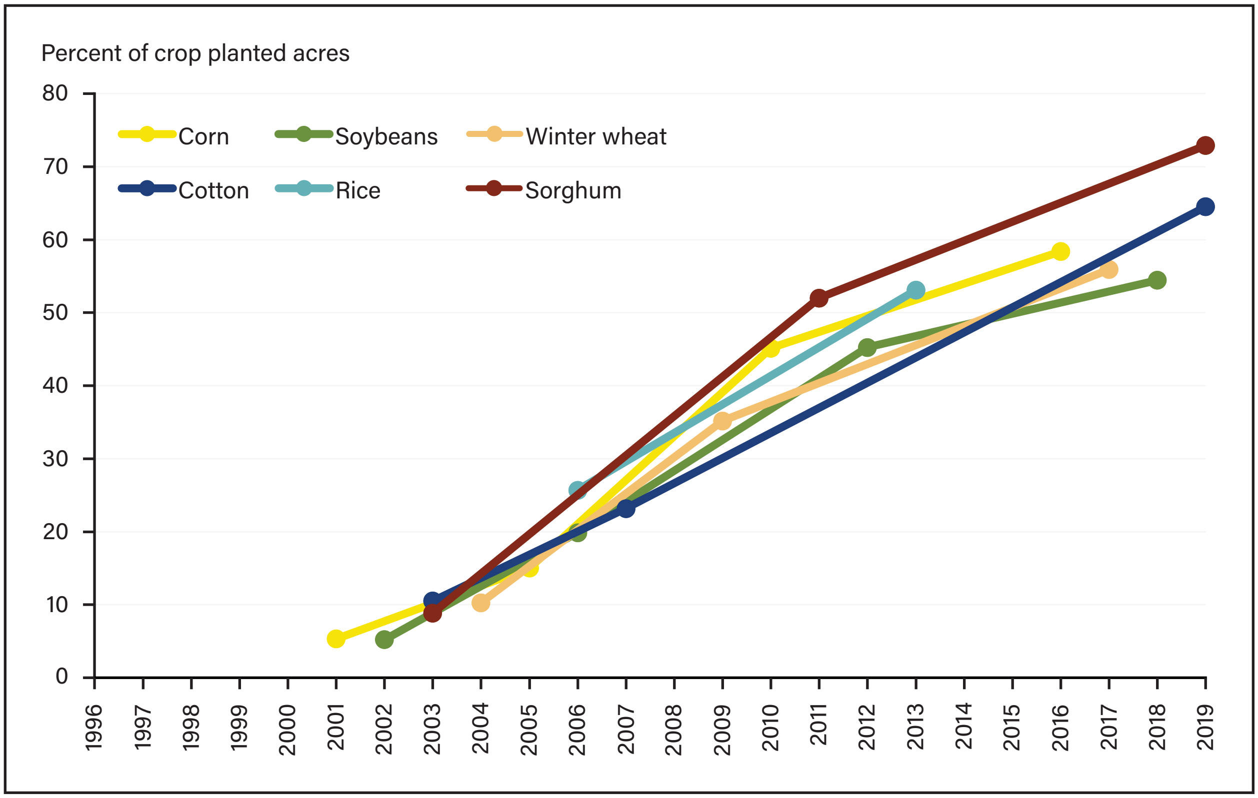
Auto-Steer and Guidance Systems

Auto-steer and guidance systems—now typically equipped with GNSS receivers—are technologies that visualize the equipment's position in the field to reduce skips and overlaps. "Manual" auto-steer systems (e.g., light bar systems) are relatively older technologies that have generally been replaced with more sophisticated automated guidance systems. The newer technologies provide for near-total automated steering of tractors, greatly freeing up farmers' time in the cab.

Such benefits, in addition to the potential for lower variable input costs from reduced skips and overlaps (e.g., for fuel, seed, nutrients, pesticides), are perhaps the reason why adoption rates have expanded rapidly since 2019, although with variation by row crop (figure 10).[8] Adoption rates by row crop ranged from 54.4 and 58.4 percent of planted soybean and corn acres in 2016 and 2018, respectively, to 64.5 and 72.9 percent of cotton- and sorghum-planted acres, respectively, in 2019.

[8] Khanal et al. (2019) found that multiple applications of GNSS guidance systems (post-adoption) would also depend on whether the technology met farmers' expectations.

Figure 10
Cropland area planted under major U.S. row crops, 1996–2019: Over half now managed with guidance systems



Note: Prior to 2018, guidance system adoption is considered to be the use of guidance auto-steering (excluding light bar systems) or use of light bar systems. Starting in 2018, guidance system adoption is considered to be only use of guidance auto-steering as data on light bar system use are no longer collected, due to its minimal use.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey, Years 2001–07, 2009–13, 2015–19.

Combinations of Technologies

In many instances, farmers use combinations of precision technologies for productivity- or cost-related reasons (Lambert et al., 2015; Schimmelpfennig, 2016; Schimmelpfennig and Ebel, 2016; Miller et al., 2019). Technology providers often give discounts on precision equipment purchased jointly rather than individually, and machinery is increasingly being sold with precision technology already embedded or as "standard" equipment through marketing practices known as bundling. Regardless of industry practices, farmers may currently be using their own combinations of technologies based on reconfigurations of various pieces of equipment acquired at different times. Using 2010 ARMS data for U.S. cornfields, Schimmelpfennig (2016) and Schimmelpfennig and Ebel (2016) found six groupings of PA technologies that were often adopted in tandem: {yield monitors + yield maps}, {yield monitors + GPS-based soil maps}, {yield monitors + guidance}, {yield monitors + yield maps + VRT}, {yield monitors + GPS-based soil maps + VRT}, and {yield monitors + guidance + VRT}. The specific reasons underlying farmers' adoption of these groupings were not surveyed, though the authors found that total input costs per acre were lower for adopters than nonadopters of each combination.

Although substantial fractions of national acreages for corn (2016), winter wheat (2017), soybeans (2018), and cotton (2019) are managed with use of only one precision technology, many technology combinations are commonly used (table 2).[9] While the {(yield and/or soil maps) + VRT} combination was used on roughly 2 percent of corn acres and 2 percent of soybean acres, use of {maps + guidance} was more pronounced, ranging from 7 percent of cotton acres to 15 percent of soybean acres. Similarly, {VRT + guidance} was jointly used on up to 12 percent of national acreage (2019 cotton), with {maps + VRT + guidance} being more common on corn acreage (23 percent) and soybean acreage (13 percent) than just {VRT + guidance}. Use of all four technologies (maps, VRT, guidance, and drones, aircraft, or satellites) occurred on 2 percent to 5 percent of national acreage across the four crops during 2016–19.

Table 2

Percent of planted acreage managed with technology combinations, 2016–19

	Survey and year			
Technology combination	Corn (2016)	Winter wheat (2017)	Soybeans (2018)	Cotton (2019)
	Percent			
Maps only	2.32	1.81	4.97	0.80
Drones, aircraft, or satellites (DAS)[1] only	0.49	0.61	0.02	0.04
Variable rate technologies (VRT) only	2.00	1.55	2.53	1.98
Guidance only	11.12	38.93	14.92	36.47
{Maps + VRT}	1.97	0.61	1.94	0.11
{Maps + guidance}	12.40	12.47	15.36	7.47
{VRT + guidance}	5.56	7.78	2.50	12.13
{Maps + DAS + guidance}	1.36	0.21	3.66	0.87
{Maps + VRT + guidance}	22.85	7.33	13.07	5.94
{Maps + DAS + VRT + guidance}	4.52	2.05	4.26	1.52

Note: DAS denote drones, aircraft, or satellites (imagery). The maps variable indicates whether the field was managed with a yield map or soil map (or both). Cells indicate the fraction of national planted acreage operated with the particular technology or combination of technologies indicated in the left-most column. USDA, National Agricultural Statistics Service (NASS)-provided expansion factors have been used to ensure the percentages are representative of national acreages. Other combinations of technologies include: {maps + DAS}, {DAS + VRT}, {DAS + guidance}, {maps + DAS + VRT}, and {DAS + VRT + guidance}. Acreage percentages for these five combinations are below 1 percent (individually) for each of the four crops, and thus, the percentages are not listed in the table.

Source: USDA, Economic Research Service and National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS), years 2016–19.

As in earlier ERS analyses, we do not pinpoint the exact reasons for the popularity of specific technology groupings. Technological complementarity (e.g., VRT reliance on mapping; mapping reliance on yield monitoring and/or soil sampling) and bundled pricing are among the most compelling economic rationales for farmers' sequential adoption behavior. At the same time, greater farm consolidation and increasing farm size may boost farmers' demand for suites of increasingly sophisticated technologies that simplify management of larger operations (MacDonald et al., 2013; Griffin et al., 2017). Determinants of individual technology adoption are explored in more depth below.

[9] Given progressively greater use of yield monitors and their installation on new combine harvesters as standard equipment, we opt to focus on other technologies that are generally more advanced and less widespread.

What Drives Farmers' Adoption of Digital Agriculture?

Economists have identified various field, farm, and operator characteristics associated with farmers' adoption of precision agriculture technologies and other digital tools (e.g., Khanna, 2021). Decades of studies have generated important insights on drivers of adoption, with emphasis centering on: field level variation in soil attributes and land characteristics, the owner-operator's level of human capital (e.g., education and years of experience) and risk perceptions, productivity or profit potential of the tool, availability of complementary (or substitutable) inputs, farm size, and behavioral preferences or other operator-specific factors (e.g., taste or distaste for technologies associated with early or late adoption). In short, many farmers' adoption decisions are based on their expectations of how the tool(s) will affect their operation's performance (see box, "How Do Precision Technologies Impact Farm Performance?"). We focus and report on several main drivers of adoption between 2016 and 2019, though with more consideration given to important factors that have been underexamined to date (e.g., technology costs, USDA programs, labor-saving benefits, and hiring of technical or consultant services).

How do Precision Technologies Impact Farm Performance?

Economists have been studying the impacts of precision agriculture on measures of U.S. farm performance for well over two decades. In general, it is conceptually difficult to generate compelling evidence on the impacts because: (1) use of real-world data from commercial farms may result in biased estimates of impacts if other confounding factors (e.g., managerial expertise, farmers' "tastes" for technologies) are not corrected, (2) use of field-trial data (typically from small samples) may result in overstated impact estimates because the carefully controlled—oftentimes ideal—conditions of experimental trials rarely occur on commercial farms. The most compelling estimates, therefore, may result from a synthesis of the two approaches, though we give preference to estimates here using large samples of commercial farms.

Among the most-studied economic dimensions of precision agriculture is profitability. Based on 2010 Agricultural Resource Management Survey (ARMS) data from U.S. corn farms, Schimmelpfennig (2016) found that global navigation satellite system (GNSS) mapping increased operating profits by almost 3 percent, while variable rate technologies' (VRT) impact was 1.1 percent. It is challenging to separate the effects of these technologies on total revenues from total costs, though revenue effects are likely the result of increased yields (Schimmelpfennig and Ebel, 2011). Such impacts are consistent with studies demonstrating that precision technologies raise the productivity of certain inputs, like nitrogen fertilizer (Isik and Khanna, 2002) and irrigation applications. These impacts are also consistent with stated motivations for the use of the technologies (Thompson et al., 2019).

Equally, if not more important, are the technological contributions to improvements in U.S. agricultural sustainability. As explained above, these technologies hold great promise for improving the environmental impacts of farming (e.g., Basso and Antle, 2020), though the evidence to date has been mixed. Adopters generally have lower input costs for fertilizers, pesticides, and fuels (which is consistent with lower use)—though reductions have been modest and vary by technology type (Schimmelpfennig and Ebel, 2016; Schimmelpfennig, 2016). Joint adopters of soil nitrate testing and crop rotations on U.S. corn fields have substantially lower fertilizer applications rates than those only adopting crop rotations (USDA, Economic Research Service, 2021). Moreover, analysis of operations on U.S. soybean and rice fields has suggested farmers who invest in precision agriculture technologies are also likely to use conservation practices, though this research does not establish a causal link between their use and a reduced environmental footprint (Schimmelpfennig, 2018; Schimmelpfennig, 2019).

continued on next page ►

continued from previous page ►

Many of these same technologies help farmers manage risk from various sources, including prices, weather, pests, and other major drivers of uncertainty throughout the growing season (Khanna, 2021). For example, late-spring soil nitrate testing is a tool to reduce uncertainty about crop nutrient needs; its use in corn production can significantly reduce fertilizer applications (Babcock and Blackmer, 1992). Similarly, farmers' use of yield and/or soil maps reduces variability in the efficiency of Midwest corn production (McFadden et al., 2022c). Risk reductions may also come about through the use of automated guidance or other input adjustments directly facilitated by guidance (Shockley et al., 2011). More broadly, it is also likely that more accurate and spatially-detailed data on input use, harvests, and growing conditions (i.e., the kind of data that underlie precision machinery and detailed management recommendations) will, over time, be useful for designing new—or improving currently existing—crop insurance products.

Technology Prices, Premiums, and Other Costs

Information on equipment replacement costs, annual fees, and premiums paid for equipment are available from ARMS surveys of soybean and cotton fields in 2018 and 2019, respectively, for yield monitors, VRT, guidance systems, and drones (table 3). Data on replacement costs are specific to yield monitors, guidance systems, and drones. Premiums paid for VRT are reported and interpreted for the entire farm operation. Annual fees are typically subscription fees (i.e., "unlock codes") that enable equipment capabilities.

Since each equipment manufacturer has company-specific pricing schedules and fee structures, costs are not homogeneous for any technology; some manufacturers are considered to be the high-cost provider for specific equipment, while other manufacturers and third-party technology providers typically have lower costs. Many farm operators do not have homogeneous equipment sets from a single manufacturer but rather an assortment from two or more manufacturers.

Since cost data in ARMS are reported for 2018 and 2019, the change in the target commodities implies vastly different acreage distributions and production practices across the 2 years. For example, half of all soybean acres in 2018 were farmed on operations with 1,105 cropland acres or fewer. By contrast, half of all cotton acres in 2019 were located on farms with 2,500 cropland acres or fewer. The costs reflect the likely number of machines for the respective crops, given that median cropland acreage on cotton farms was twice that of soybean farms.[10]

[10] However, ratios of costs to acreage differentials are similar between the soybeans and cotton data.

Table 3

Replacement costs, annual fees, or premiums associated with precision technologies, 2018–19

Technology	Cost, fee, or premium	Soybeans (2018)	Cotton (2019)
Yield monitor	Equipment replacement	$8,051	$13,775
		($350)	($1,293)
	Annual fee	$1,041	$1,772
		($76)	($482)
Variable rate technologies	Premium paid for equipment	$5,630	$10,319
		($1,320)	($3,546)
Guidance	Equipment replacement	$20,165	$25,168
		($5,019)	($2,836)
	Annual fee	$1,154	NA
		($76)	NA
Drones, aircraft, or satellites	Equipment replacement	$2,610	#
		($630)	#

Note: Entries are total dollars for equipment replacement costs, annual feels, or premium paid—depending on precision technology. Delete-a-group jackknife standard errors are reported in paratheses. The "NA" indicates data are not available; the 2019 USDA, Agricultural Resource Management Survey (ARMS) Phase II survey did not survey farmers about their annual fees for guidance systems. The "#" indicates that the sample size for equipment replacement costs associated with drones, aircraft, or satellites in the 2019 ARMS Phase II cotton survey was too small to provide a meaningful estimate.

Source: USDA, Economic Research Service and National Agricultural Statistics Service, Agricultural Resource Management Survey, years 2016–19.

Yield monitors

Yield monitor sensors for soybeans and cotton are as different as the harvesters on which they are installed. The cost of yield monitor replacement was just over $8,000 for soybeans in 2018 and $13,775 for cotton in 2019, likely a partial reflection of the difference in harvesting costs (see table 3). Moreover, acreage differences between soybean farms (especially those in the Midwest) and cotton farms in the southern United States could impact the total costs of the equipment. The annual fee for soybean ($1,041) was about half (59 percent) that of cotton ($1,772), most likely an artifact of the number of harvesters on specific crop farms.

Variable rate technologies (VRT)

VRT equipment is the same for soybeans and cotton. Therefore, no machinery differences are expected that would contribute to crop-specific VRT premiums.[11] However, the average premium paid for VRT applicators used in cotton fields in 2019 ($10,319) is double that reported by operators of soybean fields in 2018 ($5,630). As with yield monitor replacement costs, this cost differential likely reflects, at least partially, differences in the total number of VR machines implied by the difference in the acreage distribution.

An examination of per acre fees for custom variable-rate applications provides valuable insights into this segment of the equipment market. Recent custom rate surveys in the Great Plains region of the United States indicated that premium upcharges for variable rate applications (either through hire of the service itself or rental of VRT equipment) were negligible (McLure and Jansen, 2020). The survey evidence suggested that Nebraska farmers paid an additional $1.52 and $1.91 per acre (on average) for variable rate application of dry

[11] Two partial exceptions are expected. First, nitrogen fertilizers are not commonly recommended on soybean crops; thus, acre for acre, other crops (i.e., cotton, corn, and wheat) would have an additional field operation for fertilizer application relative to soybeans. Second, the price of VR planters for cotton may exceed those for soybeans, although on a "row-wise" basis, costs are not expected to be nearly double those of cotton.

and liquid fertilizer, respectively, over solid uniform rate applications. The average rental rate of VRT equipment for liquid applications was $1.17 over the average rental rate for uniform rate technology. Although the upcharge for variable rate is 20 percent above the solid uniform rate, this differential is relatively low when compared with gross production revenues on similar operations (Griffin and Traywick, 2020).

Guidance systems

Average guidance system replacement costs are higher among operators of cotton fields in 2019 compared to operators of soybean fields in 2018, likely indicative of cotton farmers' use of systems that require more expensive guidance sensors. Annual fees for guidance systems vary considerably based on guidance quality.[12] Publicly available GNSS signals are provided at zero cost for basic accuracy; however, subscription-based correction services are commonly employed by row crop farm operations. Local ground-based stations provide the highest accuracy, real-time kinematic (RTK) correction via equipment purchase or as subscription from a service provider. Satellite-based correction services are available at various accuracy levels from equipment manufacturers for combinations of activation fees and annual subscription maintenance fees.

Drones, aircraft, or satellites

Since farm operators are not expected to fund equipment replacement for U.S.-owned satellites and are unlikely to fund replacement for crewed aircraft, the $2,610 estimate in table 3 should be interpreted as pertaining to drones. Even though drones are much less commonly used than the other DA component technologies discussed in this report, their replacement costs are better understood, in large part because farm operators are likely to experience catastrophic damage (i.e., irreparable damage that renders the drone inoperable) much more often with drones than with VRT equipment or yield monitors. In addition to the drone platform, which itself can cost several thousand dollars if purchased new, the onboard camera(s) and communication devices have additional costs. Color-imaging devices are less expensive than near infrared devices or thermal sensors. Minor drone crashes may require one or more propellers to be replaced, but catastrophic damage may result in old equipment being salvaged and may require purchasing new equipment. The 2018 estimate of $2,610 is lower than the list price of new equipment in that period, suggesting that surveyed farmers may have purchased pre-owned drones (or intend to purchase pre-owned drones if their current equipment needed to be replaced).

Caveats regarding premiums, replacement costs, and annual fees

In addition to the technologies presented in the table, farmers are increasingly subscribing to cloud-based farm management information systems (FMIS), sometimes in conjunction with their service providers or input suppliers. As of 2021, one popular tool offered by the John Deere company is being marketed with a zero-subscription fee, though annual maintenance fees are still being charged for GNSS correction signals. Many of these FMIS tools are bundled with inputs and other consulting services in such a way that their incremental costs (i.e., costs solely attributable to the FMIS) are difficult—or impossible—to observe by the farm operator.

In the 1990s, technologies currently considered to be precision agriculture equipment were seldom available from the original equipment manufacturer; over the past decade, most digital technology has become standard on new equipment. For example, when a new fertilizer applicator is manufactured, VRT hardware is also installed; activation fees are then charged by the manufacturer to unlock various access levels. Similarly,

[12] Annual fees for guidance systems, as well as yield monitors, are in line with fees publicly available in catalogs of major U.S. manufacturers.

farm operators with a GNSS-enabled yield monitor in 1995 (for example) were early-stage adopters who made a deliberate effort to acquire and install the hardware. By 2015, many farm operators with yield monitors were using harvesters on which the technology had been bundled (Lambert et al., 2015; Miller et al., 2019).

Purchase prices of DA technologies are therefore more difficult to estimate today than in the 1990s when catalog prices more clearly indicated the incremental cost of the technology.[13] In many ways, several digital technologies have become inseparable from basic equipment, so adoption, replacement, and upgrade costs may be imprecisely estimated; however, one-time activation fees and annual subscription fees remain simpler to understand and can be more accurately measured.

Soil Variability and Field Topography

One of the most widely recognized determinants of farmers' precision equipment uptake is in-field soil variability (Cassman, 1999; Bongiovani and Lowenberg-DeBoer, 2004). Farmers are expected to benefit from greater awareness of spatial trends—largely through yield and soil mapping—when they have fields that exhibit high degrees of variability in soil texture, slope, organic matter, drainage, and other factors partly indicative of cropland productivity. With this knowledge, farmers can better capitalize on spatial variability by adjusting seeding, fertilizer, pesticide, and irrigation rates within the field—mainly through the use of VRT.

It is challenging to capture the full importance of soil variability and land characteristics with ARMS (Phase II) data for two reasons. First, the survey generally elicits information relevant at the whole-field level. It would be impractical to ask detailed questions on sub-field variation in soils because any responses would be necessarily general and imprecise with respect to locations within the field. Second, only management practices pertaining to one field—not multiple fields—are surveyed. This is potentially problematic because some operators condition their technology choices on soil and land variability across multiple fields. Researchers have attempted to overcome these challenges through the use of geolocated field data, but: (1) the geolocations (i.e., exact location of the field) are inaccurate for many fields, and (2) for privacy and reliability, the data must be aggregated to higher spatial levels (e.g., 3 kilometers or above), which tend to smooth out the kinds of spatial variability most important for farmers' decisions (McFadden et al., 2022c; Schimmelpfennig and Lowenberg-DeBoer, 2021).

However, the ARMS questionnaires do elicit information about whether the operator's field was nearly flat (0–2-percent grade), moderately sloped (3–9-percent grade), or steeply sloped (more than 10-percent grade). Other things being equal, greater slopes tend to coincide with lower yields, and since lower yields imply lower revenues, the operator will generally choose to adjust inputs accordingly. This input adjustment includes the possibility of taking parts of a field—or the entire field itself—temporarily out of production, in line with what is sometimes termed "zone management." Despite these considerations, adoption rates do not differ considerably by field slope (table 4). One exception is guidance systems for soybeans in 2018; adoption was 45 percent on nearly flat fields, in contrast to 26 percent on steeply-sloped fields where automated guidance may be relatively costly or impractical.[14]

[13] Regardless of year, however, catalog list prices do not include the cost of human capital investments that farmers may need to undertake to fully understand and make appropriate use of the technologies. Such prices also do not adequately capture search costs or switching costs associated with farmers' purchases.

[14] In related work, Schimmelpfennig (2018) found significant correlations between adoption of certain precision technologies and environmentally related best management practices: soil care, nutrient control, field condition monitoring, interseasonal field operations planning, and written long-term planning. These correlations were found for soybean fields from the 2012 ARMS wave, though similar findings hold for rice fields from the 2013 ARMS (Schimmelpfennig, 2013).

Table 4

Percent of surveyed fields managed with precision technologies by slope of field, 2016–19

	Yield maps	Soil maps	Variable rate technologies	Guidance	Drones, aircraft, or satellites
	Percent				
Corn (2016)					
Nearly flat	29.9 (1.9)	14.7 (1.5)	25.6 (1.8)	41.9 (2.5)	4.7 (0.8)
Moderate slope, 3–9-percent grade	27.8 (1.7)	13.1 (1.3)	23.7 (1.5)	33.9 (1.6)	3.7 (0.9)
Steep slope, over 10-percent grade	35.6 (9.6)	10.0 (4.5)	22.8 (6.2)	30.0 (7.4)	0.6 (0.6)
Winter wheat (2017)					
Nearly flat	16.7 (2.5)	5.2 (1.7)	13.0 (2.0)	46.6 (3.3)	2.0 (0.8)
Moderate slope, 3–9-percent grade	14.3 (2.0)	2.6 (0.6)	13.4 (1.6)	42.9 (3.4)	3.0 (0.1)
Steep slope, over 10-percent grade	14.4 (6.5)	6.1 (2.7)	14.8 (6.6)	36.5 (14.1)	1.9 (1.3)
Soybeans (2018)					
Nearly flat	33.8 (1.8)	13.4 (1.4)	19.5 (1.6)	44.6 (1.8)	7.3 (0.9)
Moderate slope, 3–9-percent grade	30.7 (2.2)	10.0 (1.3)	22.0 (2.1)	35.9 (2.1)	5.4 (0.9)
Steep slope, over 10-percent grade	26.2 (6.5)	7.0 (4.1)	14.8 (5.0)	25.6 (5.8)	5.6 (3.7)
Cotton (2019)					
Nearly flat	15.3 (5.3)	7.0 (1.5)	24.4 (6.0)	64.4 (3.5)	3.9 (1.1)
Moderate slope, 3–9-percent grade	9.8 (2.0)	8.3 (1.6)	24.4 (3.2)	53.8 (4.0)	2.0 (0.9)
Steep slope, over 10-percent grade	29.5 (23.1)	16.3 (14.4)	56.7 (24.4)	65.7 (20.4)	4.2 (4.7)

Note: Cell entries indicate mean adoption rates (i.e., percent of surveyed fields) by slope of field. Means have been expanded to be representative using the USDA, National Agricultural Statistics Service (NASS)-provided expansion factor (base weight). The moderately sloped category aggregates fields that have even grades and fields that have variable grades. The steeply sloped category also aggregates fields that have even and variable grades. Delete-a-group jackknife standard errors are in parentheses.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS), years 2016–19.

USDA Programs

Programs administered by the USDA and other Federal agencies have a direct bearing on farmers' input choices. For example, the Conservation Reserve Program provides an annual rental payment to contracted farmers who remove environmentally sensitive land from production (McFadden and Hoppe, 2017). More generally, many economic analyses have sought to measure the extent to which decoupled farm payments and/or federally subsidized crop insurance premiums induce changes in farmers' management practices (Weber and Key, 2012; Weber et al., 2016). However, to our knowledge, no major studies have documented the various Federal programs that directly impact digital agriculture usage, in spite of the fact that several such programs have been developed and administered in recent years.

The Conservation Stewardship Program (CSP), established in the 2008 farm bill, is a USDA working-lands conservation program that provides annual payments to participants for improving their environmental performance to address resource concerns. Some of the benefits from CSP include: enhanced resilience to weather and market volatility, decreased input usage, and improved wildlife habitats, among others. In general, a participant signs a 5-year CSP contract, which includes an opportunity to compete for contract renewal if the participant has met the initial contract requirements and agrees to achieve additional conservation goals. Contract payments, including those for enhancements involving digital agriculture, are based on (1) existing land use and stewardship at enrollment time; (2) implementation of additional conservation activities; and (3) supplementation with the adoption of one additional resource-conserving system[15] (USDA, Natural Resources Conservation Service, 2021).

Enrolled acreages for digital agriculture-related CSP enhancements that aim to improve cropland soil quality display considerable variation by practice code (table 5).[16] For example, 342,000 acres of cropland in 2017 were managed by operators who contracted to enhance their baseline stewardship by using precision pesticide applications to reduce the risk of pesticides in surface water. In 2020, this particular practice was again the most common CSP enhancement, with more than 2.24 million contracted acres, followed by 1.51 million contracted acres on which participants use precision agriculture technologies to reduce the risk of nutrient losses to surface water. Although these DA-related enhancements have become more frequently used over time, table 5 tends to overstate year-on-year growth for any particular practice because only practices on contracts signed in fiscal year 2017 or later are reported by NRCS through the RCA Data Viewer. For this reason, it is more accurate to compare contracted acres across practices within a given year.

[15] A supplemental payment is provided if the participant adopts or improves a resource-conserving crop rotation or adopts advanced grazing management (USDA, Natural Resource Conservation Service, 2021).

[16] NRCS also reports national summaries of contracted acreage for many of these same enhancements, though for other goals (e.g., improving water quality, irrigation efficiency, grazing land conservation, forest land conservation). Since NRCS performance measure rules stipulate counting any given practice in every performance measure for which it is listed (regardless of why the practice was installed), for any given DA-related CSP enhancement, acreage totals for cropland soil quality are very similar to—if not exactly equal to—acreage totals for water quality and/or irrigation efficiency (where applicable). For example, 2020 acreage totals for enhancement E449114Z1 (soil moisture is monitored, recorded, and used in decision making) are 33.66 thousand for cropland soil quality, 33.77 thousand for irrigation efficiency, and 33.77 thousand for water quality. Acreage totals for the DA-related enhancements for grazing land conservation and forest land conservation are much lower; those are not reported as they are beyond the scope of this report.

Table 5

Conservation Stewardship Program (CSP) acres for Cropland Soil Quality with enhancement practices involving digital agriculture technologies, 2017–20

	Year			
	2017	2018	2019	2020
Practice	Cropland Soil Quality per 1,000 acres Percent			
Controlled traffic farming to reduce compaction			110.60	198.00
Percent of total annual CSP Cropland Soil Quality acres			[3.05]	[3.37]
Soil moisture is monitored, recorded, and used in decision making	1.64	15.48	28.22	33.66
Percent of total annual CSP Cropland Soil Quality acres	[0.27]	[0.49]	[0.78]	[0.57]
Use precision pesticide applications to reduce risk of pesticides in surface water	341.81	1,336.27	1,055.13	2,247.15
Percent of total annual CSP Cropland Soil Quality acres	[56.61]	[42.45]	[29.13]	[38.21]
Use precision agriculture technologies to reduce risk of nutrient losses to surface water	11.66	514.45	693.04	1,514.99
Percent of total annual CSP Cropland Soil Quality acres	[1.93]	[16.34]	[19.13]	[25.76]
Use precision agriculture technologies to reduce risk of nutrient losses to ground water		0.2	10.72	51.57
Percent of total annual CSP Cropland Soil Quality acres		[0.01]	[0.30]	[0.88]

Note: Only acres for which the practice is counted toward the Cropland Soil Quality performance measure are listed. These acreage trends are similar to those for practices counted toward irrigation efficiency or water quality performance measures. Since a practice can be counted toward more than one performance measure, we do not sum acreages across measures in order to avoid double- or triple-counting. By row, the enhancement codes correspond to these five practices: E334107Z, E449114Z1, E595116X, E590118X, and E590119X, respectively. The USDA, Natural Resources Conservation Service (NRCS) is currently only reporting data based on contracts signed in fiscal year 2017 or later. Because these contracts are 5 years long and not every enhancement is implemented in the first year, there is a strong upward trend in the data over the 4 years 2017–2020—an artifact of excluding contracts signed before fiscal year 2017. Units are in 1,000s of acres. Blank cells indicate that program acreage was either zero or not reported by NRCS. Bracketed numbers are the percentages of that year's annual CSP acres for cropland soil quality represented by the particular practice.

Source: USDA, Natural Resources Conservation Service, RCA Data Viewer.

Basic economic principles suggest that farmers' decisions to enroll their acreage in one or more of these CSP practices are strongly influenced by payment rates (table 6). National payment rates in 2021 (the most recent year for which data are available) averaged $8.18/acre for controlled traffic farming, $20.85/acre for soil moisture monitoring in years 2–5 of the farmer's CSP contract, $11.45/acre for precision pesticide applications, and $15.44/acre for use of PA technologies to reduce the risk of nutrient losses to surface water.[17] As expected, this compensation represents a small fraction of annual total crop production costs, though it represents the full estimated cost to implement the enhancement. USDA estimated that national average total production costs in 2021 (excluding Government payments) were $698.73/acre for corn, $513.96/acre for soybeans, $332.26/acre for wheat, and $728.69/acre for cotton (USDA, Economic Research Service, 2022).

[17] These payment rates do not include defrayment of equipment costs. Moreover, data were not available for payments related to reducing the risk of nutrient losses to ground water, a practice reported in table 5.

Table 6

Conservation Stewardship Program (CSP) per acre payment rates for enhancement practices involving digital agriculture technologies, 2021

State	Controlled traffic farming	Advanced soil moisture monitoring, years 2–5	Precision pesticide applications to reduce risk of pesticides in surface water	Precision agriculture to reduce risk of nutrient loss to surface water
Alabama		$18.89	$11.43	$15.50
Alaska	$9.52	$25.87	$12.89	$16.81
Arizona	$8.17	$19.81	$10.77	$14.69
Arkansas	$6.97	$17.64	$10.49	$14.61
California	$9.74	$23.37	$12.15	$15.90
Colorado	$8.34	$20.52	$11.09	$14.96
Connecticut	$8.50	$21.91	$10.78	$14.40
Delaware		$21.14	$12.91	$17.03
Florida	$7.64	$17.91	$11.23	$15.29
Georgia		$18.89	$11.43	$15.50
Hawaii		$27.42	$13.35	$17.43
Idaho	$8.98	$19.04	$11.46	$15.29
Illinois		$24.52	$11.22	$14.90
Indiana	$7.46	$20.30	$10.94	$14.99
Iowa		$19.33	$11.22	$15.23
Kansas	$7.71	$19.56	$11.75	$15.80
Kentucky		$19.06	$11.13	$15.23
Louisiana	$8.34	$19.93	$10.90	$14.77
Maine		$18.73	$11.16	$15.15
Massachusetts		$25.57	$11.71	$15.57
Michigan	$8.36	$21.46	$11.88	$15.80
Minnesota		$24.46	$12.03	$15.87
Mississippi		$17.63	$11.17	$15.30
Missouri		$21.64	$11.44	$15.63
Montana		$20.99	$11.08	$15.15
Nebraska	$7.91	$19.71	$11.41	$15.42
Nevada	$7.97	$22.04	$11.10	$15.08
New Hampshire	$8.06	$19.99	$11.34	$15.28
New Jersey	$8.68	$25.56	$11.22	$15.13
New Mexico	$8.16	$17.73	$12.17	$16.15
New York	$9.02	$24.91	$12.47	$16.45
North Carolina		$18.46	$11.86	$15.85
North Dakota		$22.15	$11.14	$15.21
Ohio	$8.10	$20.92	$10.71	$14.67
Oklahoma		$18.99	$10.20	$14.05
Oregon		$23.36	$11.86	$15.65
Pennsylvania		$22.77	$12.45	$16.47
Rhode Island	$8.29	$22.70	$11.58	$15.59
South Carolina	$7.06	$18.47	$11.35	$15.55
South Dakota	$7.38	$17.76	$11.23	$15.28
Tennessee	$7.25	$17.20	$11.38	$15.47

continued on next page ►

continued from previous page ►

Texas	$8.30	$18.39	$11.46	$15.34
Utah	$7.15	$18.28	$10.09	$13.85
Vermont	$8.07	$18.31	$11.28	$15.25
Virginia	$8.25			$16.21
Washington	$9.63	$25.93	$11.84	$15.62
West Virginia		$18.38	$11.46	$15.63
Wisconsin	$8.16	$21.98	$11.40	$15.38
Wyoming		$21.14	$11.12	$15.09

Note: CSP practice codes for the four columns are E334, E449C, E595A, and E590B. None of the payment rates include partial equipment costs (e.g., "equipment and soil moisture or water level monitoring"). Multiple irrigation-related practices differentiate payment rates between year 1 and years 2–5. In four States in 2021, USDA, Natural Resources Conservation Service (NRCS) provided payments for variable rate irrigation water management associated with practice code E449 (not listed). Moreover, in 38 States in 2021, NRCS provided payments for "reducing nutrient loss by increasing setback awareness via precision technology for water quality" associated with practice code E590D (not listed). Blank cells indicate that payment rates were not reported by NRCS. No data were available for Maryland.

Source: USDA, Economic Research Service using data from USDA, Natural Resources Conservation Service, National State Payment Schedule website.

These national averages mask considerable variation in payment rates across the practices by State. For example, States with among the highest per acre payments for advanced soil moisture monitoring included Hawaii, Washington, Alaska, Massachusetts, and New Jersey (all paying well over $25/acre). By contrast, South Dakota, New Mexico, Arkansas, Mississippi, and Tennessee had among the lowest rates for this practice (offering under $18/acre). Generally, high-cost States tended to provide larger average payments, while lower cost States tended to provide smaller payments. This finding comports well with regional evidence from the annual USDA, ERS Commodity Costs and Returns data. States with high payment rates tended to be in the Heartland, Northern Crescent, and Fruitful Rim—whereas States with low rates were broadly located in the Southern Seaboard, Prairie Gateway, and Eastern Uplands (U.S. Department of Agriculture, 2022).

Alternatively, farmers can instead receive USDA assistance for one or more DA-facilitated conservation practices through the Environmental Quality Incentives Program (EQIP), which provides financial assistance (payments) to producers implementing conservation practices on working agricultural lands.[18] For each practice, NRCS defines a group of scenarios that are a set of activities that can be used to implement a specific practice. Substantial variation exists in how individual practices are applied (e.g., nutrient management plans), so there are multiple scenarios with differing costs and payments. However, NRCS no longer collects cost data for these practices directly from farmers. Although scenario-based acreage data are not available for recent years, EQIP-assisted conservation practices related to DA have lately become more popular across the United States (USDA, Natural Resources Conservation Service, 2012).

Other Government programs or initiatives have indirect "knock-on" effects that can stimulate farmers' DA adoption. For instance, broadband access to the internet is required for many digital technologies to function (or function well), and a lack of such access has been identified as a major barrier to their adoption (Whitacre et al., 2014; USDA, 2019). USDA's Rural Utilities Service has administered several programs that finance broadband and related infrastructure, including Community Connected/Reconnect Grants, the Farm Bill

[18] Three additional points should be mentioned. First, a participant is not eligible for payments for conservation practices or activities when the participant receives payments or other benefits under any other USDA conservation program for the same practice or activity on the same land at the same time. Second, EQIP payments provide financial assistance that offsets up to 90 percent of the practice implementation costs, while CSP payments typically provide 100 percent or more of the enhancement costs (and up to 10 percent of practice costs). Third, EQIP and CSP also provide technical assistance to farmers for implementing conservation practices.

Broadband Program, and the Telecommunications Infrastructure Loans and Guarantees Program. While these programs do not directly pay farmers to adopt or to improve their adoption of digital technologies, it is clear that the programs have had an accelerating effect. Astill et al. (2020) reported that USDA's Rural Development agency provided $3.4 billion of funding across 280 digital infrastructure projects between fiscal years 2010 and 2018.

Labor-Saving Benefits

Many component technologies of digital agriculture (especially autonomous machinery) are widely considered to save farmers' time and effort, a term denoted by economists as "labor-saving" (Gallardo and Sauer, 2018; Lowenberg-DeBoer et al., 2021). Automated guidance systems, for instance, can directly reduce the number of hours that operators must spend on field operations by eliminating redundant passes of equipment across cropland. Moreover, fewer workers may be needed during peak field-operating periods (e.g., during planting and harvesting). Adopters can then reallocate their "saved" hours to farm work other than field operations, off-farm work, and/or leisure.[19] The conceptual relationship between labor hours and adoption of other digital technologies is less clear. However, we would still expect an inverse relationship between labor hours and DA adoption because these technologies should contribute to enhanced decision making, likely resulting in fewer (and/or higher quality) work hours for the farmer.

Using a sample of corn fields from the 2010 ARMS, Schimmelpfennig (2016) found that total labor hours per bushel of corn for adopters of yield and georeferenced soil maps were 35 percent lower relative to those of nonadopters. Although the difference in labor hours per bushel between adopters and nonadopters of guidance systems was insignificant, labor hours per bushel were 28 percent lower for VRT adopters, as compared to nonadopters. These findings are corroborated in a sample of ARMS cornfields from 2010 and 2016 across 10 Midwestern States, as analyzed by McFadden et al. (2022c).

In that sample, labor hours per acre (totaled across the farm's entire corn enterprise) were 0.15 for adopters of yield and soil maps—half as large as the labor input for nonadopters of 0.30 hours/per acre. Moreover, adopters of guidance systems worked 49-percent fewer hours per acre than nonadopters; similarly, VRT adopters worked 41 percent less per acre than VRT nonadopters. Reductions in per bushel or per acre labor hours are unlikely to be mainly attributable to VRT adoption, however. Larger operations adopt VRT at greater rates than smaller farms, but these operations also tend to adopt other labor-saving practices (e.g., conservation tillage) and labor-saving equipment that directly embeds DA technologies (e.g., modern, ever-wider implements).

There is mixed evidence regarding per acre labor costs (Schimmelpfennig, 2016). Hired labor expenses are generally greater for adopters, while unpaid labor expenses—as measured by the operators' opportunity costs—are significantly lower for adopters than nonadopters.[20] To some extent, labor expenses have a degree of inaccuracy because implicit wage rates that underly these expenses are not quality-adjusted. Much anecdotal evidence suggests automated guidance substantially reduces operator fatigue; this improvement in the quality of fieldwork and potential improvement in quality of life for farm households—although very important—is not currently accounted for in labor-expense or labor-quantity data.

[19] Because VRT also better enables farmers to perform field operations outside of typical daylight hours, it could improve the quality of other work during daylight hours or perhaps reduce total labor hours due to a more optimized arrangement of tasks throughout the entire work cycle.

[20] As Schimmelpfennig (2016) notes, the cost of unpaid labor is estimated using whole-farm data for all types of farms. Statistical analyses of farmers' attributes (e.g., age, education, marital status, location, and other variables) are used to predict their off-farm earnings. These earnings, together with data on the total number of unpaid hours worked across the entire corn enterprise, are used to calculate the opportunity costs of farmers' unpaid labor hours.

Farm Size and Expected Productivity Impacts

Some operators adopt digital agriculture technologies for purely mechanical reasons related to farm size: Larger operations can be managed more easily and/or efficiently with high-resolution field data, automated guidance, or equipment capable of adjusting input applications in real time continuously across fields. Yet there are more nuanced reasons for the high degree of correlation between adoption and farm size.

Operations with greater cropland acreages tend to have: (1) reduced risk aversion; (2) lower per unit costs of inputs (made possible by spreading out high fixed-equipment costs over large areas, in conjunction with potential quantity discounts for input purchases that can directly reduce variable costs); (3) greater soil variability (because soil quality is generally most similar over smaller areas); (4) access to more favorable credit terms, often needed to finance the purchase of sophisticated, expensive equipment; and (5) larger numbers of managers, permitting the kind of specialization of managerial labor that could lead to greater awareness of—and expertise in using— digital technologies (Daberkow and McBride, 2003; MacDonald et al., 2013; Khanna, 2021).

Regardless of specific motivation, it is evident from the most recent data that operators of large farms adopt these tools at higher rates than operators of smaller farms (table 7). For example, only 7 percent of farms with total cropland less than 200 acres (the first quintile of cropland associated with surveyed corn fields in 2016) had an operator who adopted yield maps.[21] In contrast, 50 percent of farms with total cropland greater than 1,725 acres (the fourth quintile of cropland on farms with a surveyed corn field in 2016) had an operator who adopted yield maps. More broadly, adoption rates tend to increase with farm size, regardless of technology (maps, VRT, and guidance) or crop (corn, soybeans, wheat, and cotton).

Table 7
Percent of farms adopting precision technologies by farm size, 2016–19

	Yield maps	Soil maps	Variable rate technologies	Guidance
	Percent			
Corn (2016)				
Below 1st quintile	7	5	8	10
Between 1st and 2nd quintiles	14	6	12	18
Between 2nd and 3rd quintiles	23	11	19	35
Between 3rd and 4th quintiles	35	15	35	53
Greater than 4th quintile	50	26	43	73
Winter wheat (2017)				
Below 1st quintile	2	2	3	7
Between 1st and 2nd quintiles	8	3	9	21
Between 2nd and 3rd quintiles	22	7	21	52
Between 3rd and 4th quintiles	24	8	25	63
Greater than 4th quintile	37	10	35	82

continued on next page ►

[21] In statistics, quintiles are cut-off points that determine five groups into which a population can be divided according to the distribution of values of a specific variable. In this report, the first quintile is the acreage threshold, such that 20 percent of the surveyed fields on farms have total acreage less than this amount. The second quintile is the acreage threshold of which 40 percent of the surveyed fields are on farms with total acreage less than this amount. The quintiles differ across crops because of (1) differences in the underlying economics of each crop, (2) time-specific factors, and (3) structure of the ARMS survey.

continued from previous page ►

	Yield maps	Soil maps	Variable rate technologies	Guidance
	Percent			
Soybeans (2018)				
Below 1st quintile	11	5	9	11
Between 1st and 2nd quintiles	13	7	13	24
Between 2nd and 3rd quintiles	30	11	16	46
Between 3rd and 4th quintiles	39	15	32	65
Greater than 4th quintile	50	13	28	68
Cotton (2019)				
Below 1st quintile	7	4	17	50
Between 1st and 2nd quintiles	7	6	21	53
Between 2nd and 3rd quintiles	21	11	27	57
Between 3rd and 4th quintiles	29	7	33	66
Greater than 4th quintile	34	18	40	67

Note: Entries are a percent of farms adopting the particular precision technology (column) within each cropland acreage quintile. Due to substantial heterogeneity in farm sizes by crop, quintiles vary by crop. For corn (2016), the cropland acreage quintiles are 200, 460, 890, and 1,725. For winter wheat (2017), the cropland acreage quintiles are 300, 730, 1,600, and 3,140. For soybeans (2018), the cropland acreage quintiles are 310, 824, 1,610, and 3,430. For cotton (2019), the cropland acreage quintiles are 1,150, 1,940, 3,200, and 4,500. In statistics, quintiles are cut-off points that determine five groups into which a population can be divided according to the distribution of values of a specific variable. In this report, the first quintile is the acreage threshold for which 20 percent of the surveyed fields are on farms with total acreages less than this amount. The second quintile is the acreage threshold for which 40 percent of the surveyed fields are on farms with total acreages less than this amount. The quintiles differ across crops because of (1) differences in the underlying economics of each crop, (2) time-specific factors, and (3) structure of the ARMS survey.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service (NASS), Agricultural Resource Management Survey (ARMS), Phase II and Phase III, years 2016–19.

As discussed earlier, adoption rates are the highest for guidance systems, with notable rates of increase across the farm size distributions. On the largest farms (i.e., operation sizes at or above the fourth quintile), the adoption rate for guidance was 73 percent for corn in 2016, 82 percent for winter wheat in 2017, 68 percent for soybeans in 2018, and 67 percent for cotton in 2019. Even among the smallest cotton farms with 1,150 or fewer total acres in 2019, the adoption rate was 50 percent.

Farmers' perceptions of productivity impacts are closely related to the dimensions of farm size and its effects on adoption. Using field-level data for corn production across 10 Midwestern States, McFadden et al. (2022c) demonstrated that: (1) farmers using yield and/or soil maps are more efficient than nonadopters, and (2) these technologies increase the entire range of production possibilities. Although the effects were estimated to be small, because crop farmers' revenues are proportional to yields, we would expect these productivity effects to influence farmers' profitability. Using similar data and methods, Schimmelpfennig (2016) found small positive effects on farmers' net returns: 1.8 percent for soil and yield mapping, 1.5 percent for guidance systems, and 1.1 percent for VRT.

A simple analysis of farmers' production outcomes reveals that, in many instances, yields are statistically significantly higher for adopters than nonadopters (table 8). This trend holds across all technologies except variable rate pesticide applicators, which remain less commonly used across the United States. Differences in yields between adopters and nonadopters are generally significant for all crops except cotton and sorghum, perhaps a consequence of the relatively smaller sample sizes for both crops. Although productivity expectations are important adoption determinants, the results shown in table 8 are mere correlations between yields and technology use. They are not causal impacts because, unlike estimates from carefully implemented causal studies (Khanna, 2001; Bullock et al., 2009; Schimmelpfennig, 2016; McFadden et al., 2022c), these yield differences are not controlling for other important factors that affect yields (e.g., fertilizer quantities, growing-season weather conditions, irrigation rates, pest management, soil productivity).

Table 8
Average crop yields for adopters and nonadopters of precision technologies, 2016–19

	Yield maps	Soil maps	Variable rate seeds	Variable rate fertilizer/lime	Variable rate pesticides	Guidance	Drones, aircraft, or satellites
Corn yield (2016)							
Adopters	183***	182***	184***	187***	176**	175***	179**
	(2.87)	(4.87)	(3.39)	(3.41)	(10.5)	(2.10)	(10.79)
Nonadopters	139	147	146	143	150	137	150
	(2.13)	(2.05)	(2.19)	(2.16)	(1.81)	(2.71)	(2.19)
Winter wheat (2017)							
Adopters	62***	70***	53	58***	57	55***	51
	(2.23)	(4.34)	(3.28)	(2.95)	(4.21)	(1.41)	(12.12)
Nonadopters	46	47	58	47	48	43	48
	(1.76)	(1.54)	(1.56)	(1.62)	(1.54)	(2.07)	(1.54)
Soybeans (2018)							
Adopters	59***	59***	58***	60***	57	56***	61***
	(0.54)	(1.22)	(1.24)	(1.03)	(2.02)	(0.59)	(1.69)
Nonadopters	52	54	54	53	54	53	54
	(0.59)	(0.42)	(0.44)	(0.42)	0.46	(0.61)	(0.39)
Cotton (2019)							
Adopters	1,095**	1,067***	953	1,022	962	951	1,009
	(77.43)	(35.68)	(58.06)	(58.03)	(60.75)	(28.46)	(98.36)
Nonadopters	903	922	931	913	929	907	931
	(22.66)	(20.82)	(18.68)	(22.38)	(19.51)	(30.04)	(19.61)
Sorghum (2019)							
Adopters	82	80	78	70	78	74	99***
	(5.82)	(13.10)	(9.39)	(7.36)	(12.23)	(4.02)	(6.70)
Nonadopters	72	73	73	74	74	73	73
	(4.65)	(3.93)	(4.12)	(4.12)	(4.01)	(7.43)	(3.90)

Note: Means have been expanded to be representative of the particular crop acreage using the USDA, National Agricultural Statistics Service (NASS)-provided expansion factor (base weight). Yields for corn, winter wheat, soybeans, and sorghum are expressed in bushels/acre. Cotton yields are expressed in pounds/acre. Delete-a-group jackknife standard errors are in parentheses. Asterisks indicate if the difference in means from a two-sample *t*-test was significant at the 10-percent level (*), 5-percent level (**), or 1-percent level (***).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS), years 2016–19.

Use of Technical or Consultant Services

As precision technologies have become more complex over the previous two decades, the cost to farmers of learning about advanced machinery options has risen. As already noted, on some operations (typically larger farms), multiple owners and/or hired managers have the flexibility and human capital necessary for learning how to properly install, use, and maintain various digital agriculture technologies. Moreover, if equipment ownership provides an adoption gain, then supply chains could emerge in which larger farms purchase the equipment and rent excess capacity to smaller farms (Lu et al., 2016).

Though ARMS does not generally track whether PA technologies are owned or rented, ARMS does contain information about farmers' hiring of technical or consultant services to advise on various site-specific management practices (table 9).[22] For some farms, hiring consultant services could be a potential pathway for greater adoption if hiring the service increases operators' experience and trust with the technologies and/or reduces uncertainty about their gains from adoption (Fausti et al., 2021; McFadden et al., 2022a). Whatever the mechanism, there is a positive correlation between hiring consultant services and use of digital agriculture. Across all crops and for each type of site-specific advice service, greater shares of planted acreage were managed by adopters of any precision technology (maps, guidance, VRT, drones, aircraft, or satellites) than nonadopters. For example, 7 percent of 2016 corn acres were managed with at least one precision technology and employment of a consultant to develop/interpret a yield map or remote sensing map.[23] Similar trends, though with somewhat different percentages, prevail for the other five site-specific advisory services.

Table 9

Percent of planted acreage with hired technical or consultant services by adoption status, 2016–19

	Adopters	Nonadopters
	Percent	
Corn (2016)		
Yield map or remote sensing map development/interpretation	7.07	0.12
Soil or tissue sample collection	13.37	1.93
Nutrient recommendations/management service	13.67	2.59
Pest scouting	9.39	1.89
Pest control recommendations/management service	10.00	2.15
Irrigation management service	2.11	0.39
Winter wheat (2017)		
Yield map or remote-sensing map development/interpretation	1.50	0.09
Soil or tissue sample collection	4.99	1.99
Nutrient recommendations/management service	5.31	2.89
Pest scouting	5.11	3.03
Pest control recommendations/management service	4.15	3.34
Irrigation management service	0.59	0.15
Soybeans (2018)		
Yield map or remote sensing map development/interpretation	6.70	0.18
Soil or tissue sample collection	10.28	0.94
Nutrient recommendations/management service	11.74	1.44
Pest scouting	10.14	1.63
Pest control recommendations/management service	9.87	1.34
Irrigation management service	1.75	0.03

continued on next page ►

[22] Starting in 2018, ARMS began collecting information on whether guidance auto-steering equipment and VRT applicators were owned or leased. Of those reporting use of guidance for management of their 2018 soybean crop, 97 percent indicated they owned the technology. Similarly, of those reporting use of VRT for seeding, fertilizer/lime applications, or pesticide applications, 97 percent, 80 percent, and 90 percent (respectively) indicated they owned the applicator. For 2019 cotton, ownership rates were 98 percent for guidance auto-steering, 95 percent for VRT-seeding, 91 percent for VRT-fertilizer/lime, and 96 percent for VRT-pesticide applicators.

[23] The national acreage of PA technology nonadopters with consultant services for yield and/or remote sensing map development/interpretation must not necessarily equal zero. Shares of national acreage for PA nonadopters who hired map-related services could be nonzero if these services were hired for maps other than yield or soil maps, or for development/interpretation of yield maps for a field other than the one surveyed in ARMS. These reasons (or others) could explain the 0.12 percent of 2016 corn acreage in the first row of table 9.

continued from previous page ►

	Adopters	Nonadopters
	Percent	
Cotton (2019)		
Yield map or remote sensing map development/interpretation	3.00	0.08
Soil or tissue sample collection	11.42	1.77
Nutrient recommendations/management service	15.03	2.00
Pest scouting	21.56	4.26
Pest control recommendations/management service	19.07	2.67
Irrigation management service	4.33	0.17

Note: Cells indicate the fraction of national planted acreage managed by operators who hired technical or consultant services for the field. Adoption is defined to be whether the field was managed with maps (yield or soil); drones, aircraft, or satellites (imagery); or (VRT) variable rate technologies; or guidance. USDA, National Agricultural Statistics Service (NASS)-provided expansion factors have been used to ensure the percentages are representative of national acreages.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS), years 2016–19.

Average total per acre costs of hiring technical or consultant services were broadly higher on DA adopters' fields than DA nonadopters' fields. For adopters and nonadopters, these costs were $6.71/acre and $5.31/acre, respectively; for 2016 corn, $5.97/acre and $2.16/acre for 2017 winter wheat; $6.76/acre and $5.80/acre for 2018 soybeans; and $15.01/acre and $12.24/acre for 2019 cotton. While these average cost differentials could be partially explained by differences in the quality of services, the total number of services hired likely plays an important role: DA adopters generally hired more types of consultant services than DA nonadopters. Across the four crops, for fields on which these services were hired, the average number of services for DA adopters was 2.8–3.1, while the average for DA nonadopters was 2.1–2.6.

Data Use, Production Recommendations, and Digital Agriculture (DA)

Data from farmers' operations underlie virtually all aspects of digitalization. Because data collection is at the heart of data-driven decision making (i.e., for the use of decision-support tools), it is an integral part of digital agriculture (figure 2). To date, researchers have examined the economics of data ownership and security, anonymity and privacy, governance, and productivity effects (e.g., Coble et al., 2016; Jouanjean et al., 2020; McFadden et al., 2022b). Most analyses focus on the substantial economic potential stemming from farmers' data being collected—with or without their knowledge—for use in highly-detailed, field management recommendations (i.e., "prescriptions") for their farms and then aggregated for re-use in recommendations for operations with similar characteristics (see box, "Big Data and Digital Agriculture"). Few studies have considered, however, how farmers themselves use data from various sources, including publicly provided data and data downloads.

Big Data and Digital Agriculture

Discussions about big data in the U.S. agricultural sector have been frequently occurring among policymakers and throughout academia and the private sector since at least 2014.[1] This is mainly, though not wholly, due to the fact that most evidence-based farm management—including the use of virtually all digital agriculture tools—is based heavily on the collection, compilation, and analysis of large volumes of data. Historically, U.S. agricultural data have been "small" by conventional standards among data scientists and engineers primarily because such data have been generated mainly from surveys, experimental plots, or "one-field-at-a-time" methods. The move toward the use of much greater volumes of data delivered at much finer temporal (e.g., hourly or by the minute) and spatial (e.g., meters, feet) resolution represents a large paradigm shift in operational management and agricultural production.

For this report, big data refer to aggregations of farmers' general production activities, usually georeferenced, from millions of fields over the most detailed time unit possible (e.g., annually, monthly, daily, hourly). Such data include, but are not limited to, highly detailed information on machinery operations (e.g., type and quantity); seeding depth and rates; cultivar (type of seed); machinery diagnostics; tillage and planting dates; conservation practices; estimated pest populations, pest scouting, and pesticide spraying activities; fertilizer and irrigation applications (if any); and use of other inputs. In addition, these data are typically supplemented with information on precipitation events (e.g., rainfall, snowfall), temperature, evapotranspiration (water loss from the soil surface, crop surface, and through crop leaves), windspeeds, and other weather conditions. Moreover, these data may be supplemented with information at less finely detailed aggregations, such as operators' demographics; financial details about the farm operation and farm household; and administrative data related to participation in USDA commodity, conservation, and Federal crop insurance programs.

The many ways in which big data are transforming agriculture are, in large part, indistinguishable from the agricultural digitalization process itself. Many millions of agriculture-related data points (when analyzed and acted upon in agricultural decision making) have substantial promise for increasing farm productivity, enhancing environmental quality, and limiting downside production risk. This is because data pooled across millions of fields tend to reveal useful patterns undetectable with data from any one field. Thus, in a broad sense, the inherent value of big data is impossible to separate from the value of systemwide digitalization.

Nonetheless, a central question in analyses of the digital farm economy concerns the value of data.[2] Raw data in their original, unprocessed form often have no value—at least not until converted to information suitable for decision making. Moreover, given that data are electronic (not physical objects), identical copies of data are indistinguishable from the original; therefore, once one copy has been made available to another party, the data are no longer excludable (i.e., capable of being limited to certain market participants). In attempting to determine the value of data, it is often useful to consider the extent to which data are private goods or public goods. The use of public goods is "nonrivalrous" between consumers and "nonexcludable" from one group of consumers to another.

---

[1] There are numerous definitions, both narrow and broad, of big data. One popular definition has focused on volume, velocity (i.e., frequency of observations), and variety (i.e., available in many formats, including text) as the defining features of big data (Coble et al., 2016; Coble et al., 2018). We adopt this definition for our purposes but acknowledge that other characterizations may be equally suitable, depending on context, including those with relatively narrower or broader scope.

[2] This is partly motivated by ongoing debates centering on farmers' concerns with ownership of data originating from their fields and potential compensation for the data, in addition to concerns about data privacy and security.

continued on next page ►

continued from previous page ►

Data are considered to be a "nonrival" good because the usage of data by one consumer does not alter another consumer's ability to use the same data. Examples of nonrival data include weather forecasts from the National Weather Service or USDA, National Agricultural Statistics Service (NASS) crop production reports. Importantly, the value of data to an individual farmer is not impacted by another farmer's accessing or using the information. Farm operations and many other agribusiness entities, when given access, can consume farm data without reducing its value to the originator.

Data may also be considered "excludable" or "nonexcludable," depending upon relative access rights. Ownership of excludable goods carries a right to exclude others from obtaining access; thus, most privately held goods are excludable. For example, some weather forecasts may be privately owned and accessible only to subscribers. However, if the weather forecasts are generated with public funding and reported by a Government entity like the National Weather Service, then those data (the forecasts themselves) are nonexcludable. Agricultural data can be excludable only while it is controlled by the originating party; however, once data have been shared with any other parties or aggregated into a community, the data are no longer excludable. Excluding others from accessing and benefiting from data typically implies the forfeit of any potential network benefits that could result when significant volumes of data are pooled together for analysis.

In recent years, there have been large differences in the amount of acreage with operators who download public data relative to those who receive crop management recommendations based on data collected on their own fields (table 10).[24] Although adopters of DA components are more likely than nonadopters to download public data for use in decision making, adoption rates are low and do not vary substantially by crop. Public data downloads have tended to be highest among VRT adopters; of the 2018 soybean acres managed with VRT, 8.9 percent were operated by those who downloaded public data. Interest in public data tended to be lowest for nonadopters of guidance; of the 2017 winter wheat acres managed without guidance (just under half of all winter wheat acres that year), only 0.2 percent had operators who actively downloaded public data.

Rather, the data that farmers use from their fields tend to appear indirectly in the form of crop management recommendations,[25] which play a major role in the management practices of DA adopters.[26] For example, 63 percent of the corn acreage managed with VRT had operators who used crop management recommendations based on data from their fields. Adoption rates were relatively lower for soybeans in 2018 and cotton in 2019, though the basic trend remains: DA adopters are much more likely to make use of data-based management recommendations (and thus, implicitly, crop-productivity-related public data) than nonadopters.

[24] Due to the wording of the ARMS Phase II questionnaires in 2016–19, we do not know which types of public data farmers are downloading. However, we know that a small number of farmers are using the data to create maps. The fractions of national crop acreage managed by operators who used the downloaded data to produce maps were 3.4 percent (2016 corn), 1.4 percent (2017 winter wheat), 1.0 percent (2018 soybeans), and 0.3 percent (2019 cotton).

[25] Many privately sold management "solutions" rely extensively on detailed, publicly collected data (e.g., information about soils, yields, input and output prices, and weather).

[26] The crop management recommendations reported in this section specifically refer to recommendations based on data from the farmer's field obtained through use of a yield monitor, soil core test or soil sensor test, crop condition sensor, data from custom field work, downloaded public data, or drones, aircraft, or satellite images. These (tool-based) recommendations are conceptually distinct from (person-based) recommendations obtained by a farmer who hired technical or consultant services to advise on site-specific practices, referred to above in the subsection "Use of Technical or Consultant Services."

Table 10

Average adoption rates (percent of crop acreage) of public data downloads and crop management recommendations by adoption status, 2016–19

	Public data download	Crop management recommendations
	Percent	
Corn (2016)		
Total sample (percent of total corn acres)	2.8	29.3
Yield map and/or soil map adopters	7.8	59.4
Yield map and/or soil map nonadopters	0.7	16.1
VRT adopters	8.0	63.3
VRT nonadopters	1.2	18.3
Guidance adopters	6.6	51.2
Guidance nonadopters	0.6	16.3
Winter wheat (2017)		
Total sample (percent of total wheat acres)	1.5	22.5
Yield map and/or soil map adopters	3.8	39.8
Yield map and/or soil map nonadopters	1.0	19.1
VRT adopters	4.3	46.2
VRT nonadopters	1.1	18.9
Guidance adopters	3.2	29.0
Guidance nonadopters	0.2	17.2
Soybeans (2018)		
Total sample (percent of total soybean acres)	2.7	16.1
Yield map and/or soil map adopters	7.3	33.2
Yield map and/or soil map nonadopters	0.4	7.5
VRT adopters	8.9	35.2
VRT nonadopters	1.1	11.2
Guidance adopters	5.1	29.8
Guidance nonadopters	1.2	7.3
Cotton (2019)		
Total sample (percent of total cotton acres)	1.4	8.3
Yield map and/or soil map adopters	4.8	23.9
Yield map and/or soil map nonadopters	0.5	5.0
VRT adopters	3.2	14.9
VRT nonadopters	0.7	6.1
Guidance adopters	2.1	10.9
Guidance nonadopters	0.3	4.5

Note: VRT = Variable rate technologies. Means have been expanded to be representative of the particular crop acreage using the USDA, National Agricultural Statistics Service (NASS)-provided expansion factor (base weight). Entries are average adoption rates for public data downloads and crop management recommendations by adopters and nonadopters of precision technologies. For example, in 2016, 2.8 percent of national corn acres were managed by operators who downloaded public data, while 29.3 percent of national corn acres were managed by operators who obtained crop management recommendations. However, of the 2016 corn acres managed with either yield or soil maps (or both), 7.8 percent of such acres were operated by those who downloaded public data. Of the 2016 corn acres not managed with yield or soil maps, only 0.7 percent of such acres were operated by those who downloaded public data.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS), years 2016–19.

The fact that data-based management recommendation use is much higher than direct public data use is intuitive: Many farmers are more interested in—and better equipped for—actively making management decisions than conducting data analyses. Thus, the substantial differences could reflect farmers' relative preferences for straightforward, directly applicable business advice tailored to them based on data from their own fields similar to that provided by the Cooperative Extension Service or private input dealers. However, to a lesser extent, the differences could signal a kind of digital divide between DA adopters who are very data-savvy and those who are less so. The differences also point to the successes, at least partially, of input dealers and crop consultants. The sources of these distinctions matter as there are direct productivity implications arising from data use in crop production (McFadden et al., 2022c).

However, the value of field-level data beyond the farmgate for businesses and individuals that are not the farmer's technology providers remains uncertain. As farmers become more aware of their operational risks from data privacy and security issues, they may become more reluctant to provide their data. In recent years, ARMS has asked farmers whether they opted out of allowing their agricultural technology provider's website to share their field's data with any third party. The proportions of national acreage managed by operators who opted out of data-sharing with third parties were 5.1 percent (2016 corn), 3.4 percent (2017 winter wheat), 7.1 percent (2018 soybeans), and 9.6 percent (2019 cotton).

Conclusion

The adoption of precision agriculture technologies—basic to the ongoing digitalization of U.S. agriculture—has been rising steadily over the past two decades. The use of auto-steer and guidance systems now occurs on well over 50 percent of U.S. acreages planted to corn, soybeans, winter wheat, cotton, rice, and sorghum—up from roughly 10 percent of planted acres (or fewer) in the early 2000s. Adoption rates of other technologies (such as GNSS-based yield and soil maps, VRT, and drones) have been far less than 40 percent of planted acres, with the exception of their use in corn (in 2010) and soybeans (in 2018), the most recent years for which data are available. For winter wheat, cotton, sorghum, and rice, the adoption of these other technologies has been lower (between 5 percent and 25 percent of total U.S. planted acreage, depending on the year), though their use with these crops has still generally increased over time.

Several economic features of farmers' technology choices help to explain differences in adoption across technology by crop over time. Many of these digital tools have considerable up-front costs, repair or replacement costs, and annual user fees. These costs could be an impediment to adoption if farmers cannot "spread them out" over a large enough cropland base while earning sufficiently high revenues. USDA conservation programs providing technical or financial assistance to farmers for adopting digital agriculture technologies on working lands play a role. Certain intangible benefits like improved quality of life due to lower fatigue and stress are deemed to be major drivers of certain automation technologies, though it is difficult to quantify this relationship due to data limitations. Ultimately, key determinants of DA use are potential improvements to farmers' productivity, better environmental quality, and/or decreased exposure to downside production risks. The availability and use of technical or consultant services for providing site-specific management advice are also positively associated with farmers' DA adoption. A number of implications stem from our analysis:

First, the adoption of DA technologies on U.S. row-crop farms is far from universal. To the extent that increased productivity, improved sustainability, and enhanced risk management—individually or collectively—create valuable societal benefits above and beyond the technologies' value reflected in private markets (i.e., positive externalities), economic theory indicates there is some role for public action. Careful analysis would be needed to estimate the benefits of these technologies that are external to the farmer (if any). For example, more work is needed to quantify potential linkages between farmers' (upstream) use of variable-rate fertilizer applications and improved water quality downstream; similar research could investigate farmers' adoption of variable-rate pesticide applications and reductions in the off-target movement of agricultural chemicals. Moreover, the literature has not determined if the pricing of automated guidance systems incorporates the broader societal benefits of lower operator fatigue and reduced greenhouse gas emissions (as a result of fewer overlapping passes during field operations).

Second, it is clear from the analysis that adoption data are not available for major row crops in all years, and even among the crops with adoption data, information is not available for all technologies (including for controlled traffic farming, variable-rate irrigation, and distributed ledger technologies). Moreover, nationally representative data do not exist for DA adoption in livestock and specialty crop agriculture. Filling this gap in our understanding of DA uptake in those sectors would thus appear to be a significant priority. Large input firms in DA marketplaces (e.g., Bayer, John Deere) are collecting increasingly large amounts of data directly from farmers' fields.

While this direct data collection holds some potential, many caveats currently exist. Data from input firms via farm equipment or smart applications may not be: (1) accurate (equipment may not be calibrated correctly); (2) representative (e.g., farmers differ with respect to brand loyalty); (3) accessible (e.g., firms are not likely to share microdata with policymakers and researchers); or (4) comprehensive (e.g., equipment does not capture operator demographics, farm household income and assets, and off-farm labor).

A third implication from the analysis is that the role of skills and human capital formation as precursors to DA adoption should not be overlooked. Much has already been written on digital divides between operators who are technologically savvy and those who are not. The latter group may increasingly miss opportunities for DA-facilitated improvements to farm performance as digitalization deepens in the coming decade. However, such divides may somewhat lessen over time as younger generations, increasingly digital natives who are technologically savvy, displace older generations in the agricultural workforce. Nonetheless, the nature of day-to-day farming operations is likely to change—potentially drastically—as automation becomes more commonplace; thus, more analysis is needed to determine whether and to what extent skill-building programs are needed for the agricultural labor force.

Fourth, DA nonadoption tends to be correlated with smaller farm sizes, lower crop yields, less use of crop management recommendations, and limited employment of technical or consultant services for various reasons that cannot be solely attributed to the lack of DA uptake. This places renewed focus on recurring policy interest in the linkages between technical change and structural change. Past research has provided compelling arguments for the case that conventional precision agriculture—alongside larger and faster equipment, no-till practices, genetically engineered seeds, and other innovations—has contributed to larger farm sizes (MacDonald et al., 2013). Yet, if autonomous robots prove to be scale-neutral, their commercialization and widespread use could push against the trend of greater crop and livestock consolidation (MacDonald et al., 2018; Lowenberg-DeBoer et al., 2020). Such a scenario, however, would not necessarily reverse the consolidation trend—especially if new technologies are developed and released that continue to favor larger farms and operators with perhaps greater technical skill sets.

References

Acemoglu, D., and P. Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives* 33(2):3–30.

Astill, G., A. Perez, and S. Thornsbury. 2020. *Developing Automation and Mechanization for Specialty Crops: A Review of U.S. Department of Agriculture Programs. A Report to Congress*, AP-82, U.S. Department of Agriculture, Economic Research Service.

Babcock, B.A., and A. Blackmer. 1992. "The Value of Reducing Temporal Input Nonuniformities," *Journal of Agricultural and Resource Economics* 17(2):335–347.

Basso, B., and J. Antle. 2020. "Digital Agriculture to Design Sustainable Agricultural Systems," *Nature Sustainability* 3:254–256.

Basso, B., C. Fiorentino, D. Cammarano, G. Cafiero, and J. Dardanelli. 2012. "Analysis of Rainfall Distribution on Spatial and Temporal Patterns of Wheat Yield in Mediterranean Environment," *European Journal of Agronomy* 41:52–65.

Bongiovani, R., and J. Lowenberg-DeBoer. 2004. "Precision Agriculture and Sustainability," *Precision Agriculture* 5:359–387.

Bullock, D.S., M.L. Ruffo, D.G. Bullock, and G.A. Bollero. 2009. "The Value of Variable Rate Technology: An Information-Theoretic Approach," *American Journal of Agricultural Economic*s 91(1):209–223.

Cassman, K.G. 1999. "Ecological Intensification of Cereal Production Systems: Yield Potential, Soil Quality, and Precision Agriculture," *Proceedings of the National Academy of Sciences* 96(11):5952–5959.

Castillo, M., S. Simnitt, G. Astill, and T. Minor. 2021. *Examining the Growth in Seasonal Agricultural H-2A Labor*, EIB 226, U.S. Department of Agriculture, Economic Research Service.

Coble, K., T. Griffin, M. Ahearn, S. Ferrell, J. McFadden, S. Sonka, and J. Fulton. 2016. "Advancing U.S. Agricultural Competitiveness with Big Data and Agricultural Economic Market Information, Analysis, and Research." The Council on Food, Agriculture & Resource Economics, Washington, DC.

Coble, K.H., A.K. Mishra, S. Ferrell, and T. Griffin. 2018. "Big Data in Agriculture: A Challenge for the Future," *Applied Economic Perspectives and Policy* 40(1):79–96.

Daberkow, S.G., and W.D. McBride. 2003. "Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture in the US," *Precision Agricultur*e 4:163–177.

DeBoe, G., and M. Jouanjean. 2019. "Digital Opportunities for Better Agricultural Policies." Organisation for Economic Co-operation and Development, Paris, France.

Erickson, B., J. Lowenberg-DeBoer, and J. Bradford. 2017. "2017 Precision Agriculture Dealership Survey." Department of Agricultural Economics and Agronomy, Purdue University.

Erickson, B., J. Lowenberg-DeBoer, and J. Bradford. 2020. "2020 Precision Agriculture Dealership Survey." Department of Agricultural Economics and Agronomy, Purdue University.

Food and Agriculture Organization of the United Nations (FAO). 2020. "Realizing the Potential of Digitalization to Improve the Agri-Food System - Proposing a New International Digital Council for Food and Agriculture: A Concept Note." Food and Agriculture Organization of the United Nations, Rome, Italy.

Fausti, S.W., B. Erickson, D.E. Clay, and S.A. Clay. 2021. "The Custom Service Industry's Role in Precision Agriculture Adoption: A Literature Review," *Journal of the Western Agricultural Economics Association* 19(2):58–67.

Gallardo, R.K., and J. Sauer. 2018. "Adoption of Labor-Saving Technologies in Agriculture," *Annual Review of Resource Economics* 10:185–206.

Gasso, V., C.A.G. Sørensen, F.W. Oudshoorn, and O. Green. 2013. "Controlled Traffic Farming: A Review of the Environmental Impacts," *European Journal of Agronomy* 48:66–73.

Graff, G.D., F. de Figuerado Silva, and D. Zilberman. 2021. Venture Capital and the Transformation of Private R&D for Agriculture, in P. Moser, editor, *Economics of Research and innovation in Agriculture*. National Bureau of Economic Research, Cambridge, MA: University of Chicago Press.

Griffin, T.W., J.P. Brown, and J. Lowenberg-DeBoer. 2007. *Yield Monitor Data Analysis Protocol: A Primer in the Management and Analysis of Precision Agriculture Data*. Department of Agricultural Economics and Agribusiness, Cooperative Extension Service, University of Arkansas and Department of Agricultural Economics, Purdue University.

Griffin, T.W., K.D. Harris, J.K. Ward, L.P. Goeringer, and J.A. Richard. 2022. "Three Digital Agriculture Problems in Cotton Solved by Distributed Ledger Technology," *Applied Economic Perspectives and Policy* 44(1):237–252.

Griffin, T.W., J. Lowenberg-DeBoer, D.M. Lambert, J. Peone, T. Payne, and S.G. Daberkow. 2004. *Adoption, Profitability, and Making Better Use of Precision Farming Data*. Department of Agricultural Economics and Agronomy, Purdue University.

Griffin, T.W., N.J. Miller, J. Bergtold, A. Shanoyan, A. Sharda, and I.A. Ciampitti. 2017. "Farm's Sequence of Adoption of Information-Intensive Precision Agricultural Technology," *Applied Engineering in Agriculture* 33(4):521–527.

Griffin, T.W., and L.S. Traywick. 2020. "The Role of Variable Rate Technology in Fertilizer Usage," *Journal of Applied Farm Economics* 3(2):59–67.

Isik, M., and M. Khanna. 2002. "Variable-Rate Nitrogen Application Under Uncertainty: Implications for Profitability and Nitrogen Use," *Journal of Agricultural and Resource Economics* 27(1):1–16.

Jouanjean, M., F. Casalini, L. Wiseman, and E. Gray. 2020. *Issues around Data Governance in the Digital Transformation of Agriculture: The Farmers' Perspective*. OECD Food, Agriculture, and Fisheries Papers Number 146, Organisation for Economic Co-operation and Development, Paris, France.

Khanal, A.R., A.K. Mishra, D.M. Lambert, and K.P. Paudel. 2019. "Modeling Post Adoption Decision in Precision Agriculture: A Bayesian Approach," *Computers and Electronics in Agriculture* 162:466–474.

Khanna, M. 2021. "Digital Transformation of the Agricultural Sector: Pathways, Drivers, and Policy Implications," *Applied Economic Perspectives and Policy* 43(4):1221–1242.

Khanna, M. 2001. “Sequential Adoption of Site-Specific Technologies and its Implications for Nitrogen Productivity: A Double Selectivity Model,” *American Journal of Agricultural Economics* 83(1):35–51.

Lacoste, M., S. Cook, M. McNee, D. Gale, J. Ingram, V. Bellon-Maurel, T. MacMillan, R. Sylvester-Bradley, D. Kindred, R. Bramley, N. Tremblay, L. Longchamps, L. Thompson, J. Ruiz, F. Garcia, B. Maxwell, T. Griffin, T. Oberthür, C. Huyghe, W. Zhang, and J. McNamara. 2022. “On-Farm Experimentation to Transform Global Agriculture,” *Nature Food* 3:11–18.

Lambert, D.M., K.P. Paudel, and J.A. Larson. 2015. “Bundled Adoption of Precision Agriculture Technologies by Cotton Producers,” *Journal of Agricultural and Resource Economics* 40(2):325–345.

Lamm, F.R., M.D. Dukes, K.C. Stone, and B.Q. Mecham. 2021. *Beyond 2020, Vision of the Future: Selected Papers from the Sixth Decennial National Irrigation Symposium*, in Transactions of the ASABE, 6th Decennial National Irrigation Symposium, 1449–1458.

Lowenberg-DeBoer, J., and B. Erickson. 2019. “Setting the Record Straight on Precision Adoption,” *Agronomy Journal* 111(4):1552–1569.

Lowenberg-DeBoer, J., I.Y. Huang, V. Grigoriadis, and S. Blackmore. 2020. “Economics of Robots and Automation in Field Crop Production,” *Precision Agriculture* 21:278–299.

Lu, L., T. Reardon, and D. Zilberman. 2016. “Supply Chain Design and Adoption of Indivisible Technology,” *American Journal of Agricultural Economics* 98(5):1419–1431.

MacDonald, J.M., R.A. Hoppe, and D. Newton. 2018. *Three Decades of Consolidation in U.S. Agriculture*, EIB-189, U.S. Department of Agriculture, Economic Research Service.

MacDonald, J.M., P. Korb, and R.A. Hoppe. 2013. *Farm Size and the Organization of U.S. Crop Farming*, ERR-152, U.S. Department of Agriculture, Economic Research Service.

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. “On Digital Soil Mapping,” *Geoderma* 117(1–2):3–52.

McFadden, J.R., and R.A. Hoppe. 2017. *The Evolving Distribution of Payments from Commodity, Conservation, and Federal Crop Insurance Programs*, EIB 184, U.S. Department of Agriculture, Economic Research Service.

McFadden, J.R., F. Casalini, and J. Antón. 2022a. *Policies to Bolster Trust in Agricultural Digitalisation*, OECD Food, Agriculture, and Fisheries Papers Number 175, Organisation for Economic Co-operation and Development, Paris, France.

McFadden, J., F. Casalini, T. Griffin, and J. Antón. 2022b. *The Digitalisation of Agriculture: A Literature Review and Emerging Issues*, OECD Food, Agriculture, and Fisheries Papers Number 176, Organisation for Economic Co-operation and Development, Paris, France.

McFadden, J.R., A. Rosburg, and E. Njuki. 2022c. “Information Inputs and Technical Efficiency in Midwest Corn Production: Evidence from Farmers’ Use of Yield and Soil Maps,” *American Journal of Agricultural Economics* 104(2):589–612.

McHugh, A.D., J. Tullberg, and D.M. Freebairn. 2009. “Controlled Farming Restores Soil Structure,” *Soil and Tillage Research* 104(1):164–172.

McLure, G.A., and J.A. Jansen. 2020. *2020 Nebraska Farm Custom Rates*. EC823, University of Nebraska Extension, Lincoln, NE.

Miller, B.A. 2017. “Geographic Information Systems and Spatial Statistics Applied for Soil Mapping: A Contribution to Land Use Management,” in P. Pereira, M. Muñoz-Rojas, E. C. Brevik, and B. A. Miller, eds. *Soil Mapping and Process Modeling for Sustainable Land Use Management*. Elsevier.

Miller, N.J., T.W. Griffin, I. Ciampitti, and A. Sharda. 2019. “Farm Adoption of Embodied Knowledge and Information Intensive Precision Agriculture Technology Bundles,” *Precision Agriculture* 20(2):348–361.

Porter, W.M., J.A. Rascon, Y. Shi, R.K. Taylor, and P.A. Weckler. 2013. “Laboratory Evaluation of a Turn Compensation Control System for a Ground Sprayer,” *Applied Engineering in Agriculture* 29(5):655–662.

Saavoss, M., T. Capehart, W. McBride, and A. Effland. 2021. *Trends in Production Practices and Costs of the U.S. Corn Sector*, ERR 294, U.S. Department of Agriculture, Economic Research Service.

Schimmelpfennig, D. 2018. “Crop Production Costs, Profits, and Ecosystem Stewardship with Precision Agriculture,” *Journal of Agricultural and Applied Economics* 50(1):81–103.

Schimmelpfennig, D. 2016. *Farm Profits and Adoption of Precision Agriculture*, ERR 217, U.S. Department of Agriculture, Economic Research Service.

Schimmelpfennig, D. 2019. “Improvements in On-Farm Resource Stewardship with Profitable Information Technologies in Rice Production,” *Journal of Environmental Economics and Policy* 8(3):250–267.

Schimmelpfennig, D., and R. Ebel. 2011. *On the Doorstep of the Information Age: Recent Adoption of Precision Agriculture*, EIB-80, U.S. Department of Agriculture, Economic Research Service.

Schimmelpfennig, D., and R. Ebel. 2016. “Sequential Adoption and Cost Savings from Precision Agriculture,” *Journal of Agricultural and Resource Economics* 41(1):97–115.

Schimmelpfennig, D., and J. Lowenberg-DeBoer. 2021. “Precision Agriculture Adoption, Farm Size, and Soil Variability,” in J. V. Stafford, editor, Proceedings on the 13th European Conference on Precision Agriculture, Precision Agriculture ’21. Wageningen Academic Publishers.

Shockley, J.M., C.R. Dillon, and T.S. Stombaugh. 2011. “A Whole Farm Analysis of the Influence of Auto-Steer Navigation on Net Returns, Risk, and Production Practices,” *Journal of Agricultural and Applied Economics* 43(1):57–75.

Thompson, N.M., C. Bir, D.A. Widmar, and J.R. Mintert. 2019. “Farmer Perceptions of Precision Agriculture Technology Benefits,” *Journal of Agricultural and Applied Economics* 51(1):142–163.

United Nations. 2022. “World Population Prospects,” United Nations Department of Economic and Social Affairs, Population Division, New York, NY.

USDA. 2019. *A Case for Rural Broadband: Insights on Rural Broadband Infrastructure and Next Generation Precision Agricultural Technologies*, American Broadband Initiative, U.S. Department of Agriculture, Washington, DC.

USDA, Economic Research Service. 2021. *ARMS Farm Financial and Crop Production Practices*, U.S. Department of Agriculture, Economic Research Service, Washington, DC.

USDA, Economic Research Service. 2022. *Commodity Costs and Returns*, U.S. Department of Agriculture, Economic Research Service, Washington, DC.

USDA, Natural Resources Conservation Service. 2012. *Partnership Initiative with ACES for Precision Farming 2021 Incentive*, U.S. Department of Agriculture, Natural Resources Conservation Service, Washington, DC.

USDA, Natural Resources Conservation Service. 2021. *RCA Data Viewer*, U.S. Department of Agriculture, Natural Resources Conservation Service, Washington, DC.

Vellidis, G., C.D. Perry, G.C. Rains, D.L. Thomas, N. Wells, and C.K. Kvien. 2003. "Simultaneous Assessment of Cotton Yield Monitors," *Applied Engineering in Agriculture* 19(3):259–272.

Weber, J.G., and N. Key. 2012. "How much do Decoupled Payments Affect Production? An Instrumental Variable Approach with Panel Data," *American Journal of Agricultural Economics* 94(1):52–66.

Weber, J.G., N. Key, and E.J. O'Donoghue. 2016. "Does Federal Crop Insurance Make Environmental Externalities from Agriculture Worse?," *Journal of the Association of Environmental and Resource Economics* 3(3):707–742.

Whitacre, B.E., T.B. Mark, and T.W. Griffin. 2014. "How Connected are our Farms?," *Choices* 29(3):1–9.

Whitt, C., J.E. Todd, and A. Keller. 2021. *America's Diverse Family Farms*, EIB 231, U.S. Department of Agriculture, Economic Research Service.

Appendix: Overview of DA Component Technologies

Yield maps and soil maps

Sensor and other data associated with geospatial coordinates from global navigation satellite systems (GNSS) provide the information needed to create maps. Farm operators then use computerized yield and soil maps to customize farm management decisions (e.g., McFadden et al., 2022c).

For yield maps, instantaneous mass flow sensors detect grain flow in combine harvesters or seed cotton on cotton pickers. Harvester-mounted sensors on grain combines usually measure force per unit of time (e.g., pounds per second) in the clean grain elevator, and modern sensors on cotton harvesters use microwave technology to detect cotton lint moving through the vacuum shoot. Sensor data (including mass flow, moisture, GNSS coordinates, and harvester machine data such as swath width, logging duration, and elevation) are recorded on local logging devices and pushed to cloud-based systems in near real-time via telematics over wireless communication systems (e.g., cellular devices). Grain-yield monitor sensors predate the advent of GNSS, but modern cotton-yield monitors were first commercialized for the 2000 growing season (Vellidis et al., 2003). Other than cotton, combines harvest the crops reported in this study.

Post-processing for quality assurance of yield data is often necessary for on-farm research, input application prescriptions, meeting conservation compliance requirements, and other farming activities, especially for flagging erroneously measured observations for omission and geographically adjusting data points to compensate for flow delays (Griffin et al., 2007).

For soil maps, physical and chemical characteristics of within-field variability may be mapped from a combination of publicly available and personally held sources, such as chemical analyses from precision soil sampling. Soil chemical characteristics from laboratory analysis of soil samples include nutrient levels, pH, and percent organic matter and are typically personally held by the farm operator, crop consultant, and/or landowner. Precision soil sampling implies multiple soil samples taken across a field, usually at less than 10 acres per sample or on predefined sub-field management zones. Management zones may be based on a combination of soil mapping units, previous yield history, prior soil test results, topography, or other yield-affecting factors. By 2017, two-thirds of precision soil samples were 2.5-acre grids, followed by 5-acre and 1-acre samples (Erickson et al., 2017). Soil physical characteristics may include texture, water holding capacity, apparent electrical conductivity, soil surface color, and combinations of the factors from publicly available USDA NRCS soil surveys.

Soil maps are associated with the adoption of map-based variable rate technologies that require knowledge of site-specific soil nutrient requirements. Soil nutrient and physical characteristic maps have been used to determine optimal input rates of fertilizer and seeds—and to justify alternative land uses, such as soil conservation or rotation into noncropping systems.

Variable rate technologies (VRT)

Variable rate technologies (VRT) are equipment that can provide customized applications of seeds, lime, fertilizers, or crop protection chemicals such as herbicides, insecticides, and other pesticides at specific sites. Their purpose is in contrast to status quo uniform rate technologies (URT) that only allow for uniform input applications within or across the field. Some farm operators consider VRT to underlie the application of site-specific, prescription-based rates of inputs within individual fields—while others consider VRT to underlie applications that are uniform within each field but vary across fields. The latter concept (inter-field VRT) was possible before civilian access to GNSS; however, the former (intra-field VRT) became feasible with the advent of GNSS in the early 1990s.

Intra-field VRT is usually accomplished with GNSS-enabled automated controllers mounted within the machinery and/or tractor for map-based or on-the-go applications. Map-based VRT applications rely upon preprocessed prescriptions based on geo-referenced yield, soil, imagery, topography, and in-field scouting data. On-the-go VRT (such as Trimble's GreenSeeker) relies, at least in part, on real-time sensor data processed via algorithms rather than human intervention. One form of within-field VRT allows distinct input types to be applied on-the-go or via map-based prescriptions; specifically, these forms are multiple-cultivar planters that place crop varieties at precise locations within the field during an individual pass through the field.

As-applied data collected from sensors provide information on how much product was applied at each site-specific location. These as-applied data are useful for farm management recordkeeping, on-farm experimentation, regulatory compliance, and crop share lease negotiations.

Guidance systems

Guidance systems have included manual control (i.e., lightbars that help the operator understand the equipment's position in the field) and automated guidance for parallel or contour passes. The main distinction between manual and automated control is that the latter obviates the need for the equipment operator to make manual adjustments with the steering wheel through the field. Even with fully automated guidance, however, the equipment operator must turn the equipment around near field boundaries.

GNSS-enabled harvesters, sprayers, and tractors replaces manual-operator labor with autonomous control that can reduce operator errors and fatigue while potentially improving quality-of-life of rural households. Guidance systems with manual control (i.e., lightbars) were commercialized in the mid-1990s but subsequently replaced by automated guidance in the late 1990s for most field operations. GNSS-enabled guidance systems have become standard features of equipment used for row crops, and by 2021, the guidance receivers were fully integrated into the cabs of equipment for at least one major manufacturer.

Guidance systems have incidental benefits for farm data. High accuracy GNSS systems log elevation data that may be useful for developing topographical maps for modeling watershed, variable rate prescriptions, and land-forming operations. These data are being collected on passes through the field from harvesters, tractors, sprayers, and other equipment.

Drones, aircraft, or satellite imagery

Imagery is a form of remotely-sensed data collected from satellite, crewed aircraft, and small unmanned aerial vehicles (UAVs), i.e., fixed-wing and rotorcraft drones. Imagery from remotely sensed sources has been available for farm management purposes for many decades. The U.S. Landsat satellites provided publicly available imagery during the 1970s, though imagery from film cameras via hot-air balloons predated satellite imagery by several decades. Renewed interest in commercializing imagery data has arisen from the availability of drones due to the reductions in lithium battery prices.

Imagery has been available in black and white, true color (i.e., from RGB, which mixes the primary colors red, green, and blue to produce a range of other colors), and in multiple variations of normalized difference vegetative indices (NDVI, which measures and assesses changes in vegetation greenness and density using near infrared and thermal infrared). Pixel resolution tends to be inversely proportional to the age and elevation of the sensor. The temporal resolution of imaging data has traditionally been a limitation to practitioners (i.e., image capturing may not occur on desired dates or during a desired series of dates).

Automated section control

Automated section control is associated with liquid sprayers and planters. An automated boom section or nozzle on sprayers and row shutoffs on planters are examples of automated section control. Automated section control can be considered an on-the-go form of VRT, where the rates are “zero” or “full.” Control sections automatically shut off while associated portions of equipment are in specific subfield areas that do not need any input applications (e.g., areas that have already received applications), and it keeps remaining control sections operating on areas where the application is intended. Control sections may be a section of the application boom or planter bar or a single nozzle or planter row-unit.

Coverage maps and GNSS information

The benefits of automated section control tend to be associated with field geometries nearly opposite those favoring automated guidance. The kinds of irregular field geometries that benefit from section control are those that require portions of equipment booms or planter rows to be on large areas with diverse needs (e.g., some subareas require input applications, while other subareas do not) as the machine moves along the transect.

Multiple machines can implement automated section control by coverage map-sharing technology. Coverage map sharing allows two or more machines to share data regarding where applications have already been made, usually in real time via local area networks (LANs) but more typically via wireless cellular providers. For in-field coverage maps, sharing has been implemented between planters, sprayers, and harvesting systems since 2016.

Turn compensation is a special case of automated section control, typically on sprayers (Porter et al., 2013) and planters, that adjusts the targeted application rate for each nozzle or row-unit independently to either more closely match a variable-rate prescription or account for differences in actual travel speed due to matching turning at some radial degree. Turn compensation is the specific technology that changes the rates for individual nozzles along the boom as the sprayer or row units on the planter move along a contour pass;

this technology can be considered a form of VRT along the boom or planter bar. Turn compensation became feasible on planters with the advent of electric drive row units and on sprayers with the introduction of pulse width modulation (PWM—a system in which each nozzle has a pulsing device that adjusts its flow rate).

Controlled traffic farming, tramlines

Controlled traffic farming (CTF) is a practice that limits the soil surface of the field from experiencing wheel tire or track traffic, usually establishing tramlines so that individual, repeatable passes of farm equipment return to the same tire tracks each trip across the field for as many field operations as possible. To be considered controlled traffic, the proportion of the field with tire traffic is limited to less than 25 percent of the soil surface. Tramlines usually do not receive seed during planting under the assumption that those areas will not be productive, given that the routine traffic would destroy any plant growth. Reducing soil compaction across the field from equipment passes has been a leading incentive for farm operators to adopt controlled traffic farming, especially in regions without freeze and thaw cycles (Gasso et al., 2013; Griffin et al., 2004; McHugh et al., 2009).

Farmers in the United States have adopted controlled traffic farming at lower rates than those in Australia, Canada, Europe, and other parts of the world; however, the technique has been used as a conservation practice for several decades in parts of the United States and is somewhat gaining in popularity nationwide. Automated guidance has empowered farm operators to adopt CTF by reducing the complexity of establishing tramlines. One ancillary benefit of tramlines is that many farm operations that rely upon GNSS automated guidance can continue operating in the event of a GNSS outage, given quasi-permanent visual tramlines.

Telematics and wireless data transfer

Telematics is the wireless transfer of data between farm equipment, connected devices, and/or the cloud either via local area networks, e.g., Bluetooth, or cellular systems. Data transferred may be prescription maps sent to applicators or as-applied maps of seeds, chemicals, or fertilizers, sensor data (yield monitor data), or coverage maps. Remote monitoring of field equipment is possible via telematics. Farm data are typically collected from technology while the machinery is performing intended operations in the field and pushed to the cloud; however, an important exception is downloading prescription maps to VRT applicators.

Due to residential user behavior, internet service providers typically calibrate speeds to favor data downloads rather than uploads; however, field operations typically require uploads of various large files and downloads of only relatively small map-based prescription files to VRT applicators (Whitacre et al., 2014). Less than 40 percent of agricultural service providers implemented telematics in their business operations in 2020 (Erickson et al., 2020). The first telematics devices were available for agricultural equipment as early as 2002 and, for at least one major equipment manufacturer, became standard in 2011.

Calibration of wireless connectivity for agricultural purposes (i.e., data uploads) requires adequate connectivity. Yet in crop producing regions, wireless connectivity may be weak or nonexistent, especially if fields are not within proximity of interstate highways or municipalities (Whitacre et al., 2014). There is debate about whether next-generation connectivity will be useful for agricultural purposes, which hinges on (1) the extent to which 5G networks will have geographical coverage similar to that of earlier 3G and 4G networks, and (2) whether satellite internet services will provide sufficient latency.

Telematics improve farm data systems—both within and beyond the farmgate—by automating the otherwise-tedious, manual process of physically moving flash media from farm equipment to office computers. Although the physical transfer of flash media is an uncomplicated task, barriers to optimal data use have resulted from loss of small flash-media cards.