Digital Transformation for a Sustainable Agriculture in the US: Opportunities and Challenges

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1. Introduction

With the growing global population and urbanization, declining availability of land for agriculture, depletion of water resources, and looming threat of climate change, the agricultural sector faces the critical challenge of meeting growing demands on land sustainably. Increasing crop productivity by increasing the efficiency of input use and conserving water and chemicals can potentially reduce acreage and adverse impacts on the environment. However, to intensify production sustainably, crop management decisions need to be site-specific because agricultural landscapes are characterized by considerable heterogeneity in growing conditions and variability over time. Conventional practices for producing cash crops, like corn, soybeans, and wheat in the US, rely on intensive tillage practices, uniform rates of applying critical inputs, such as nitrogen and irrigation water, and the aerial spray of pesticides to reduce weeds and pests that disregard cropland's spatial and temporal variability.

Irrigated agricultural production in the many states with the largest amount of irrigated acres in the US relies primarily on groundwater which depletes aquifers, including the Ogallala aquifer leading to salinization (USGAO, 2019). Fertilizer-intensive corn production in the Midwest is a leading cause of nutrient run-off and the growing problem of hypoxia in the Gulf of Mexico (Rabotyagov et al., 2014). Nonpoint pollution sources from agriculture have been estimated to contribute over 90% of the nitrogen in two-thirds of all nitrogen-impaired watersheds in the United States (Ribaudo et al., 1999). Excessive use of chemicals with herbicide tolerant corn and soybeans is contributing to a rising problem of herbicide-resistant weeds (Davis and Frisvold, 2017). Furthermore, agricultural production in the midwestern US that relies on conventional tillage practices has decreased soil organic carbon substantially since 1850 levels, and large areas continue to decrease soil carbon (Yu et al., 2018). In addition, agricultural production continues to contribute to carbon emissions, chiefly from livestock production, direct energy use, and emissions of nitrous oxide from soil (Parton et al., 2015). Midwestern farmland is currently also responsible for the vast majority of fertilizer run-off and greenhouse gas emissions (Basso et al., 2009). It is estimated that cropland mineral soils have lost 30%-50% of the carbon stocks in the top-soil layers relative to their native condition (Paustian et al., 2019). Farming has also destroyed fertile topsoil by leading to soil erosion, and this contributes to lower crop yields, loss of ecosystem services, and affects the global carbon cycle. Zhang et al., (2015) estimate that soil erosion has led to a loss of organic-rich soils from a third of the Midwestern Corn Belt, contributing to a 6% reduction in crop yields and $2.8 billion losses on average annual economic losses.

Current strategies for applying critical inputs, such as nitrogen and irrigation water, disregard the spatial variability in soil and growing conditions across the field and temporal information about weather. This results in over-application in some areas, and under-application in other areas relative to the required amounts and compromises crop productivity while adversely affecting the environment. Fertilizer is often applied after harvest in the Fall when it is cheaper, and labor is available, resulting in significant nutrient run-off before crops can take it up in the Spring. Limited availability and high cost of labor pose a barrier to adopting practices that can enable more targeted and timely application of these inputs. With conventional practices, about 40% of irrigation water applied using flood and furrow methods is not taken up by plants and is drained away from the field (Brouwer et al., 1989). Zhang et al., (2015) estimate that only 68% of the applied nitrogen is absorbed by crops in the US and the rest is surplus that runs-off.

Use of herbicides for weed control has grown exponentially, driven by price declines and lower labor requirements of using herbicides compared to mechanical weeding using tractors. From 1952 to 2008, the percentage of corn, wheat and cotton acres treated with herbicides rose from 5-10% to 90-99% (USDA ERS 2014). The popularity of glyphosate-resistant crops has led to a heavy reliance on glyphosate and a reduction in the diversity of weed management tools, further reducing the adoption of IPM in weeds (Livingston et al., 2016). In a 2007 survey, Frisvold et al., (2009) found that 28% of farmers rarely or never used herbicides with different while 39% modes of action and respondents practiced it often or always. Herbicides are typically sprayed prior to the emergence of the plant and/or prior to the closure of the crop canopy; they are therefore not targeted to where and when weeds appear and have resulted in a reduction in the diversity of weeds and an increase in glyphosate resistant weeds.

Although the labor intensity of agricultural production has been declining over time, the sector faces a shortage of labor and rising real wages of agricultural workers (Zahniser et al., 2018). The US farm labor market is expected to further tighten in the coming years with economic development and continued transition to the service sector in the US and in Mexico, a major source for immigrant farmworkers and tightening of immigration laws in the US. Some crops rely more on labor for agricultural operations than others; overall, contract and hired labor together accounted for 10%[1] In 2017, the Great Plains, Midwest, and Southeast accounted for 37% of the labor employed in agriculture. These trends in the agricultural labor market are creating a demand for making farming more autonomous using robotics and artificial intelligence (AI) technologies.

The advent of digital technologies that offer information and computational tools has the potential to detect, quantify and enable site-specific management practices that apply the "*right*

[1] This share is 4.5% for oilseed and grain farming but as high as 40% for greenhouse, nursery, and floriculture production and fruit and tree nut farming (Zahniser et al., 2018)

seed and the right input application rate with the *right soil* at the *right* time." This can increase the efficiency of input use, increase crop productivity and reduce environmental harm (Wolfert et al., 2017). Digitally enabled agricultural technologies enable the collection of vast amounts of geo-referenced information about growing conditions within a field that can be analyzed using machine learning, and other artificial intelligence (AI) approaches (van Es and Woodard, 2017). These technologies use electronic information to gather, process, and analyze spatial and temporal data and combine it with precision agricultural technologies that facilitate automated implementation of spatially varying input applications (Lowenberg-DeBoer et al., 2020). They allow monitoring and detection of variability in crop health, soil fertility, and yields in the field and have the potential to vary input application rates based on the precise location of fertility levels and crop requirements in a field. Recommendations for crop management based on this information can be fed to on-board technologies, such as Variable Rate Technologies (VRT), to apply inputs at varying rates through a field. These technologies can digitally record observations for a field and share this electronically information with crop advisors and input supplies and reduce the need for manual labor.

Additionally, emerging AI technologies have the potential to use machine intelligence to address the labor shortage challenge using advanced autonomous systems with low-cost robots, sensors, and other auto-steered and guided equipment to precisely guide equipment and enable site-specific input placement and application rates to manage heterogeneity and variability within fields. Small robots can be deployed to undertake operations, such as killing weeds, applying nitrogen, or planting cover crop seed under the canopy of field crops that are not feasible with conventional field equipment.

While these technologies offer the advantage of site-specific crop management with varying levels of autonomy, their adoption can impose financial costs and require learning, investment in new equipment and skills, and sharing data with technology and input suppliers. Furthermore, the benefits of these technologies to farmers are still uncertain and yet to be demonstrated, and adoption decisions are likely to be influenced by information sources that farmers trust, such as neighbors and peers. The policy incentives to induce adoption by rewarding farmers for the external benefits from adoption to the environment are yet to emerge and require demonstrated evidence of these benefits. Adoption of digital technologies also requires the availability of enabling infrastructures such as access to broadband, availability of technology providers, and technical assistance.

This paper has three objectives. First, we describe some emerging digital technologies that provide alternative approaches to address the challenge of herbicide resistant weeds, over-application of nitrogen and irrigation water, and cover crop planting. We also discuss how these technologies can contribute to the environmental sustainability of agriculture. Second, we discuss the factors likely to affect adopting these technologies relative to conventional approaches. Since these technologies are yet to be widely adopted and some are yet to become commercially available, there is limited literature examining the drivers of adopting digital and AI technologies. We discuss insights from the literature on economic factors, behavioral preferences of farmers, peer pressure, and social networks that can be expected to play a role in adoption decisions.

Third, we discuss methods for analyzing the adoption of digital technologies even before they are widely adopted. These methods need to consider that adoption of new technologies is often not a discrete choice problem; instead, farmers may adopt technologies gradually following on-farm trails and learning by doing on a small share of their land. Often technologies that consist of many components that can be adopted individually are not adopted as a complete package; instead, farmers adopt components sequentially as they learn about the benefits of various components. We discuss various options for surveying farmers to determine the drivers of the extent and mix of technology adoption decisions. Since these are hypothetical decisions and the technologies being considered are multi-dimensional in terms of their attributes and performance outcomes, choice experiment survey methods that go beyond open-ended questions about the discrete adoption decision are more informative about the trade-offs farmer are willing to make about various technology attributes and performance outcomes and the economic and behavioral drivers of adoption. We also discuss modeling approaches to extrapolate from survey respondents to a regional level and examine the likely drivers of technology diffusion in the region while incorporating empirical evidence on both economic and behavioral drivers from the survey. Specifically, agent-based models (ABMs) offer an approach for modeling the behavior of a collection of autonomous decision-makers (agents) that are individually assessing a situation and making decisions on the basis of a set of rules and interactions with other agents. ABMs are useful for modeling complex behavior patterns that evolve over time and allow for learning, adaptation, and idiosyncrasies. We conclude with a discussion of the policies needed to cost-effectively induce the adoption of digital technologies to make agriculture more sustainable.

2. Challenges to Sustainable Agricultural Production

Low Input-Use Efficiency

Conventional methods for determining input application rates are typically based on average growing conditions in the field and disregard spatial variability within fields due to differences in soil quality, topography, soil moisture, and other locational characteristics. Zhang et al., (2021) report that most farmers typically make decisions about irrigation timing and the amount by relying on their personal experience, weather forecast, visual observation, and their neighbors' behavior; surveys report that fewer than 25% of irrigation scheduling methods are based on science and technology, resulting in over- or under-irrigation. The former leads to wastage of water and polluting run-off, while the latter may result in crop water deficit, lower yields, and economic loss.

Similarly, recommendations for nitrogen application rates have been based on conditions at a regional level and on yield potential and broad management zones within fields. There is also empirical evidence that farmers consistently over-apply fertilizer due to the belief that it could otherwise be the factor limiting crop yield if expectations of favorable weather are realized (Basso et al., 2009); this is the case even when yield data imply that an increase in fertilizer applications increases yield variability (Paulson and Babcock, 2010). Uniform application rates for fertilizer using conventional technologies can lead to over-fertilization in some areas and under-fertilization in other areas. The former can lead to high salt concentration in the soil, damage to the root system of plants, degradation of soil health and increase in nutrient loss to surface and groundwater while the latter can result in crop nutrition stress, potential yield loss, and profit reduction. Nitrogen use efficiency in cereal grain production is low and a significant share of applied nitrogen is lost through denitrification, run off and volatilization of ammonia (Raun and Johnson, 1999). Despite efforts to increase nitrogen use efficiency in agriculture, it continues to remain low. Basso et al., (2019) estimate that it could be as low as 33%, particularly on subfields that can be classified as having stable low yields or unstable yields.

Research shows that crop yields vary widely within fields and variable rate of input application has the potential to provide both environmental benefits for society and economic benefits for farmers (Ruffo et al., 2006). High resolution spatial data from fields cultivated with maize, soybean, wheat and cotton in the US Midwest show that wide variations in crop productivity within a field; some areas produce more than others and with different levels of fluctuation in annual yields these variations across the field depend on the interaction between climate, soil, topography and management (Maestrini and Basso, 2018). Basso et al., (2019) used eight years of high-resolution satellite imagery, at subfield resolutions of 30 × 30 m across 30 million ha of 10 Midwest states to show that on average, 26% of subfields in the region could be classified as stable low yield, 28% as unstable (low yield some years, high others), and 46% as stable high yield.

Moreover, there has been limited understanding of the processes within fields that control crop response to inputs. These processes vary spatially and temporally, and determining which site-specific characteristics determine corn yield response to nitrogen has been challenging[2]. Moreover, the agronomic knowledge needed to respond to observed heterogeneity in growing conditions in the field and to develop recommendations for varying input applications has lagged behind the engineering capabilities of technology to manage fields more flexibly (van Es and Woodard, 2017). As a result, although VRT for nitrogen application have been available since the mid-1990s, adoption rates have been low (Babcock and Pautsch, 1998; Liu et al., 2006). Precise knowledge of spatial variability factors are essential to estimate economic benefit of VRT over conventional approaches based on net improvement in crop yield with adaptation of VRT (Bullock et al., 2002). Studies and survey results find that only 16-26% of the U.S. corn and soybean farms applied VRT (Schimmelpfennig, 2016). Some of the reasons include farmers cannot process the available farm information data to make the optimal decision, margin

[2] https://water.unl.edu/documents/Section%20E.pdf

revenues from the site-specific application are not attractive enough, and alternative systems like the light bar systems and automatic guidance systems are developed (Pedersen and Lind, 2017).

Herbicide Resistant Weeds

Corn, soybean, and wheat production rely heavily on herbicides for weed management. Chemical herbicides are relatively low cost and easy to apply pre-emergence and post-emergence by equipment on the field or through spraying (Schutte et al., 2010). The effectiveness of herbicides at killing weeds has been declining. The productivity of pesticide use in the US has declined by more than 50% in the past three decades, while herbicide use intensity has been increasing for corn, cotton, rice, and wheat. Growing weed resistance is imposing a net cost on corn, soybean, and cotton of about $1 billion per year. This is particularly concerning because no new commercial herbicide modes of action have been discovered in more than 30 years. Although industry has been developing crop varieties tolerate to multiple modes of action, many weed species are already resistance to these modes and thus stacking herbicide tolerant traits is likely to be ineffective (Frisvold et al., 2017). Herbicide resistance management requires reducing selection pressure through lower levels of herbicide use, substituting non-chemical means of control and rotation or mixing alternative herbicides with different modes of action (Davis and Frisvold, 2017). Non-chemical means of herbicide control, other than manual weeding, include tillage and grazing; these can have other unintended negative environmental consequences such as soil compaction, loss of soil carbon, soil erosion, and therefore reduced water quality (Deynze et al., 2021).

Low Soil Carbon Stocks and Soil Health

Most agricultural soils are depleted in soil carbon compared to native ecosystems due to intensive soil disturbance, soil erosion, nutrient depletion and removal of harvested biomass. Various best management practices can improve soil carbon stocks, including planting of highresidue crops, seasonal cover crops, green manure, continuous cropping (reduced fallow frequency), and planting of permanent or rotated perennial grasses. Cover crops can either be planted in fallow seasons or planted as an intercropping practice and terminated before planting cash crops in the Spring with the cover crop biomass mixed with the upper soil surface or be harvested for further economical use.

Cover crops have the potential to increase soil microbial activity, soil nitrogen and phosphorous availability to crops (Giuliano et al., 2021). This can reduce the need for additional fertilizer and can increase crop yield (Lowry et al., 2021). Cover crop planting has also been reported to improve soil quality and soil health compared to frequently tilled management (Ramos et al., 2010). The magnitude of positive effect from cover crop may differ based on the soil type (Snapp et al., 2005). Additionally, large scale cover cropping practice can provide climate change mitigation benefits by sequestering atmospheric carbon in soil that are larger than with no-till practice alone (Kaye and Quemada, 2017). Planting cover crops can decrease weed cover and lower weed biomass (Christina et al., 2021), reduce soil compaction and tillage needs, improve soil moisture management and provide income from livestock grazing and sale of animal feed.

Farmers have an incentive to adopt cover crops because of the perceived benefits such as soil health improvement, soil erosion abatement, yield boosts, and reduced risk associated with loss of nutrients into waterways and savings in costs of fertlizers and herbicides by enabling natural nutrient recycling and weed control (Arbuckle Jr and Roesch-Mcnally, 2015; Plastina et al., 2020). However, Plastina et al., (2020) report yield losses from cover crop planting in initial years if farmers have limited knowledge of cover crop management and choice of cover crop variety and till soil fertility improves. High management costs of seeding and terminating cover crops and low costs of fertlizers and herbicides also limit the economic benefits of cover crops (Bergtold et al., 2019). Currently, cover crop planting remains a minority practice with over 95% of farmland soil left completely bare after the harvest of corn and soybeans in the early Fall and vulnerable to soil erosion and chemical run-off (Zulauf and Brown, 2019). A survey of farmers in Illinois, Indiana, Iowa and Minnesota by Singer et al., (2007) finds that about a third of farmers did not plant cover crops due to time and cost constraints. Low emergence and biomass of cover crops due to late planting after harvesting operations and the conflict between planting cover crops and other higher priority farm operations after harvest (such as spraying, soil preparation and fertilizer application) are other barriers to cover crop planting.

3. The Imperative for Digital Agriculture for Sustainable Agricultural Production

Advances in digital agricultural technologies, remote sensing, soil sensors and drones and AI have the potential to enable farmers to gather, process, store and analyze vast amounts of data from millions of acres and then use AI to process the data into relevant and easily interpretable information that can guide decisions. Farm machinery companies are using telematics to wirelessly transfer data from field equipment to a centralized database where machine learning methods can study patterns in crop responses to various genetic traits, environmental conditions and management practices and develop site-specific recommendations for crop management. These technologies have the potential to overcome many of the challenges described above, including (a) provide site and time specific recommendations for input application to jointly reduce two main sources of uncertainty that affect farming operations – variations in soil conditions and topography and the weather (b) lower labor requirements for farm operations, such as tilling, harvesting, cover crop planting and weed control and (c) provide non-chemical approaches to manage weeds. We describe these opportunities below.

Implement Site-and Time-Specific Input Applications

Precision Irrigation

Multiple irrigation technologies are available to farmers to increase efficiency of water use and avoid over-irrigation, including micro-irrigation, sprinkler and drip systems. Farmers can also use precision irrigation systems, such as soil moisture sensors, computer or smartphone decision support tools, and remote control of irrigation equipment to help optimize irrigation scheduling. Center pivot irrigation system can be designed to know exactly how fast to move and where water is most needed at any given moment. Variable rate irrigation systems gather field data including crop type, development stage of the crop, soil type, grade of the land, and weather information, and use that information to distribute water as effectively as possible. This allows farms to control water distribution by zone, speed, and individual sprinkler at each degree of the 360 degree circle, which prevents watering areas that do not need it. A number of precision irrigation decision support products are available that estimate crop water needs and soil water balance for irrigation scheduling which can even be done for a few days ahead by incorporate information from weather forecasts (see Zhang et al., 2021).

To determine the precise amount of water to be supplied to plants at critical stages during the growing season requires understanding of crop water needs, soil water holding capacity, evapotranspiration rates, irrigation system capacity and the supply of moisture to plants across the field and at different times during the season. There are various devices to measure soil moisture, evapotranspiration rates and obtain real time weather data. Precision irrigation methods rely on multiple sources of data: in-situ data, remotely sensed data as well as gridded data on weather, soil and climate data. Soil sensors provide measurements of soil moisture, soil temperature, soil salinity and other soil conditions at a field scale while weather sensors deployed by weather stations provide information about meteorological conditions. Remote sensing data characterize canopy conditions at a larger scale, across space and time, such as vegetation indices, leaf area index and canopy temperature. This information is used to develop soil-based and plant-based metrics for determining irrigation timing by quantifying the maximum allowable depletion of soil water capacity that plants can tolerate and the level of crop water stress. In addition to measurement-based approaches, process models combined with gridded weather, climate and soil data and daily evapotranspiration reports can be used to determine soil water balance and crop water use and develop irrigation schedules with lead time of a few days with weather forecasts. This information can be combined with other information within a decision support system on a smartphone or a computer to obtain a recommendation or prescription on when to irrigate and how much. These recommendations can then be implemented using technologies that allow remote control of farm equipment such as remote pivot controls that enable control of irrigation systems using a smartphone or a computer to start and stop pivots, adjust pivot speeds and monitor system's location. Additionally, variable rate technology can enable farmers to vary watering intervals and amounts for different zones of their field by using GPS.

There are several technological challenges that need to be overcome for effective application of precision irrigation decision-support systems. Firstly, in-situ sensors are costly, and they can be labor-intensive to install and remove before and after a growing season. They provide point specific estimates rather than capturing spatial heterogeneity in the field. While satellite-based data can provide data on vegetation conditions they lack the spatial and temporal resolution needed for accurate irrigation application decisions. Secondly, the ability to quantify plant water stress in the field based on soil conditions is limited because these metrics are not able to consider atmospheric conditions. Third, there are large uncertainties and lack of generalizability in the ability of process-based models to predict crop water needs precisely within a field (see detailed review in Zhang et al., (2021). As a result, adoption rates of precision irrigation technologies have been growing but is still low. By 2013, it is estimated that less than 10% of farms surveyed used a soil or plant-based moisture sensing device or a commercial irrigation scheduling service as a method for deciding when to irrigate. Variable rate irrigation technology was used on about 28% of corn acres in 2016 and on 11% of wheat acres in 2009 (USGAO, 2019).

Variable Rate Nitrogen Application

Determining the right amount of nitrogen to apply at specific locations of a field is challenging because it depends on fixed environmental factors, such as soil texture and N availability as well as time varying factors such as temperature, rainfall amount and timing. Environmental (E) factors, management (M) factors such as planting, and nitrogen application dates and genetic (G) factors of corn variety interact in non-linear ways to determine crop nutrient needs. To understand crop nutrient response, high spatial resolution data on crop yields and combinations of GxExM are needed together with machine learning algorithms, to develop generalizable methods for predicting nutrient management practices that vary by G and E at a sub-field level. Digital technologies are enabling the implementation of this approach using "big data" from millions of acres of cropland to provide the diversity in G, E and M to develop agronomic knowledge to respond to sub-field heterogeneity. Data on soil factors, weather conditions, canopy health indicators along with machine learning algorithms are being used to make fertilizer application recommendations and implemented using VRT.

Variable rate nitrogen applications can be based on prescriptive information, such as historical yield maps or real-time parameters (Khakbazan et al., 2021; Shi et al., 2020) based on remote sensing technologies and other real-time and non-destructive nitrogen detection methods (Tang et al., 2018). The latest generations of portable monitors are able to carry different types of real-time sensors and obtain remote sensing data accurately and quickly (Lan et al., 2019), but this is still at an experimental stage. Remote sensing measurements are affected by temperature, illumination, and other field conditions which can restrict the accuracy of the biological information that is obtained about crop characteristics. The enormous amount of remotely sensed data about crop characteristics at various stages of growth by hyperspectral imagers and Lidar sensors require immense computing power and advanced computer hardware in order to rapidly process data in real time. Current sensors are still too expensive to be widely applied and this limits applications of VRT.

Reduce Labor Requirements

Labor shortages are a major concern in the agricultural sector in the US. About 73% of farm labor in the US is foreign born and much of this is seasonal labor and undocumented labor.[3] Tightening immigration laws and declining supply of immigrant workers and domestic workers seeking agricultural jobs are creating an increasing demand for automation of agricultural operations. Automation can reduce labor costs, allow for faster operations in a given period of time, reduce labor fatigue, increase the precision with which farming operations are conducted and reduce risks due to uncertainties about labor supply. A promising area for deploying a team of robots is for cover crop planting. Utracompact, undercanopy robots can plant cover crops as early as August while the annual crop is still in the field and thereby provide sufficient time for establishment of cover crops and generation of high biomass. These robots are expected to

[3] https://www.asme.org/topics-resources/content/automating-the-risk-out-of-farming

require minimal human oversight and eliminate time conflicts with other post harvest field operations.

Non-Chemical Approaches to Manage Weeds

Conventional herbicides are typically applied before the canopy closes and decisions about herbicide application rates are restricted to the early stage of the growing season (i.e., pre- and post-emergence of the crop). The resulting spraying threshold is time-invariant and not a function of time-varying density of weeds. Small agricultural robots are being designed to drive between two rows of crops even after the canopy closes, detect the weeds by their in-built cameras, and use "a course bristle on a robot arm" to pull and break the root of the young weeds. These weeding robots can be timed to traverse the fields and eliminate weeds before they start to spread seeds, and hence, reduce the next generation of weeds. They can also kill late-emergence weeds (i.e., weed that emerges after crop canopy closes) and thereby mitigate crop yield loss (McAllister et al., 2019). Post-emergence herbicide effectiveness can be limited when weeds are too large and when the crop is in later stages of growth. It also depends on environmental conditions which influence the absorption of herbicides and potential for crop injury (Livingston et al., 2016). Robots can improve weeding efficiency and work long hours in an optimized manner with uninterrupted and predictable performance (Uyeh et al., 2021). In addition, because of their size and weight, these robots do not cause soil compaction and erosion. The long-term benefits of robotic weeding include the delay of resistance where it has not occurred, reducing a key barrier to the adoption of beneficial conservation tillage which can otherwise increase weeds and the environmental and health benefits of lower herbicide use (Deynze et al., 2021).

In the future, robots are expected to play a significant role in precision farming beyond weeding by enabling site-specific fertilization, seeding, field diagnosis, and phenotyping. Several aspects of robotic technology are still under development, including their navigational capabilities in conditions where row spacing and field conditions are irregular and plants are not precisely planted, the ability to operate with high levels of autonomy (without requiring human monitoring) and being able to eliminate weeds without damaging the crops (Carrington, 2021).

4. Economic and Behavioral Drivers of Adoption

Profitability

The economic incentives to adopt digital technologies are expected, at least in part, to depend on their costs and benefits relative to conventional methods of farming. According to the threshold model of adoption a risk-neutral farmer is likely to adopt these technologies if they increase yield and lower variable input costs and if the net savings in operating profits are greater than the annualized costs of adopting the new technology. The extent to which these technologies increase yield and lead to input cost savings will vary across locations, crops, crop varieties and technologies as well as over time depending on weather conditions. Differences in soil, climate and other biophysical characteristics of their farm, the extent of variability in these characteristics, farm size, human capital availability and other factors will determine the economic outcomes of adoption. These factors affect the extent to which a technology is output-enhancing and/or input-conserving (Caswell and Zilberman, 1986).

The effects of technologies that increase input-use efficiency on yields, input-use and profits will depend on spatially heterogenous factors such as soil characteristics (slope, nutrient content, texture), technology characteristics and input and output prices. Typically, only a portion of the applied input is effectively used and the extent to which this is the case depends on soil characteristics. Caswell and Zilberman, (1986) show that efficient irrigation technologies are more likely to be adopted in locations with low and quality and when water cost if high. They are likely to increase yields in areas where soil quality is low, but they may also increase water use per acre, groundwater extraction and overall water consumption on the farm (Grafton et al., 2018). While these technologies may reduce applied input use per unit yield, they may increase total yields, lead to a switch to more input-intensive crops and make it profitable to expand cultivation on non-cropland. Isik and Khanna, (2002) identified that site specific application of nitrogen may decrese overall nitrogen application, prevent over-application, and reduce nitrate run off to water bodies. However, success of variable rate nitrogen application in croplands rely upon the cropland and weather information systems and yield variability data, reduction in their uncertainties can potentially increase benefit of site-specific fertilizer application.

A review of precision irrigation studies in the US shows that quantitative estimates of water savings by adopting variable-rate sprinklers range from 10% to 15% compared to conventional furrow and entire field surface irrigation using center pivots (Sadler et al., 2005). In addition, some studies show benefits of increased harvestable area, lowered disease incidence by eliminating water-logged conditions, and reduced leaching of nutrients with precision irrigation technologies. Adeyemi et al., (2017) report potential for reaping substantial benefits in terms of yield improvements and water savings if optimal irrigation scheduling i.e., the right time and quantity of irrigation water to be applied, can be incorporated into current precision irrigation management. They argue that existing research has emphasized sensing and control features for managing spatial variability in crop and soil water requirements with limited research on irrigation scheduling. An upgraded technology that incorporates real-time data on soil, plant, and weather for model predictive control can enable appropriate scheduling of irrigation. However, yield benefits of precision irrigation depend on soil characteristics and previous irrigation management strategies. For example, DeJonge et al., (2007) find their precision irrigation i.e., automatic application when required by individual grid, to have slightly lower corn yields than uniform scheduled irrigation with center pivot system on loamy soils in the US.

There have been several field experiments in the US to examine the agronomic and economic consequences of implementing VRT for nitrogen application. Some studies find that it can lead to higher yields and reduced costs compared to uniform application; the extent to which this is the case depends on the uniform rate that is applied and the within-field variation in soil properties, such as top soil depth (Wang et al., 2003). Other studies do not find similar benefits from VRT compared to applying the same amount of fertilizer at a uniform rate (Ferguson et al., 2002).

The profitability of using robots for cover crops will depend on the costs of using robots for planting cover crops and the benefits they provide in terms of improving establishment of cover crops and thereby reducing weeds, improving soil health and crop productivity, compared to conventional methods. Using robots for intra-row weeding in both the organic and conventional farming reduce herbicide and can mitigate yield losses due to herbicide-resistant weeds. The economic benefits will depend on avoided yield damages; these depend on weed density (Swinton and King, 1994), frequency with which weeds emerge during the growing season (Wu and Owen, 2014), number of days weeds survive in the field (Steckel and Sprague, 2004), and herbicide resistance level (Livingston et al., 2016). Weeding robots can operate throughout the growing season, even after the plant canopy closes, and thus have greater effectiveness at killing weeds before they start to cause damage or produce seeds. The cost of adopting robotic weed control compared to herbicides will depend on a number of factors such as, the cost of robots, then number of robots needed, the level of autonomy of the robot and whether robots need to be owned or can be rented from technology providers.

Risks and Uncertainties of Adoption

In addition to the profitability of crop production with alternative technologies, the riskiness of those profits can also affect decisions about adoption by risk averse farmers (Just and Zilberman, 1983). Risk-averse farmers value higher profits but associate negative benefits to the riskiness (frequently measured by variance) of those profits. By providing recommendations for input application rates (particularly for inputs such as fertilizer which are risk increasing) based on precise and geo-coded information about production conditions on the field and real time weather information, digital technologies can reduce the riskiness of production. The extent to which this is the case will depend on the ability of digital technologies to provide precise information about growing conditions and management responses to observed conditions. Uncertainty about the accuracy of precision technologies and risk preferences of farmers can reduce the benefits of adopting these technologies for farmers and the environment (Isik and Khanna, 2002). High capital and learning costs of adoption and uncertainty about how to specifically respond to information about growing conditions can also increase the risks of farm operations.

Uncertainty about the benefits and/or costs of adopting a technology that involves large sunk costs and are largely irreversible can affect decisions about the timing of adoption. Digital technologies are still undergoing development and improvements and their costs can be expected to decline and performance improve with economies of scale in production and learning by doing. Increased use of these technologies in the future are likely to improve the accuracy of recommendations for site specific management, the effectiveness of weed removal and cover crop planting. In such cases, the literature on investment decisions under uncertainty shows that there is a value to keeping the option of adoption at a later date and to delay adoption until the expected benefits of adoption are sufficiently higher than the expected costs. Farmers that have high discount rates may be less willing to adopt a technology with high upfront costs and whose benefits are uncertain and may be realized over a long horizon (Khanna et al., 2017, 2000).

Partial and/or Sequential Adoption

Digital technologies include many components, data acquisition technologies, data analysis technologies and precision application technologies, and offer many choices (e.g the level of autonomy of equipment). Not all farmers will adopt all components at once or adopt on all of their land at the same time. Farmers prefer to customize their adoption decisions to meet their individual needs and to adopt on a small portion of their land first as a learning mechanism and then expand adoption. Studies show they often prefer to adopt technologies sequentially based on risk considerations, supply constraints, and due to a lack of knowledge about their costs and benefits (Khanna, 2001). Data acquisition technologies may be adopted first because they can inform information management decisions about the benefits of precision application for a range of inputs, including fertilizer, herbicides, pesticides, and irrigation. Data analytics and precision application equipment is likely to be adopted if the spatial variability in growing conditions is large enough to make it beneficial to adopt VRT. Applicative technologies may then be adopted more selectively to manage particular management needs. The components adopted may also depend on farm size the scale neutrality of the technology. Some technologies such as soil sensors are and small robots are scale neutral and more likely to be adopted even by smaller farmers while other technologies like VRT equipment if more likely to be adopted by larger, more experienced and innovative farmers with greater human capital skills. Weersink and Fulton, (2020) describe the agricultural technology adoption process as a multi-stage process including information awareness, non-trial evaluation, field experimentation, initial adoption, re-evaluation, and eventual continuity or disadoption. The factors that affect each of the stages of adoption differ: profitability is important determinant in the later stages of adoption whereas social and cognitive considerations are more important in early stages of adoption since novel technology requires adaptation and acclimatization with initial costs prohibiting positive net returns initially. Trialability is also important in the learning process to reduce high uncertainty associated with adopting a novel agricultural technology (Chavas and Nauges, 2020). Learning from extension agents, input providers, neighbors (peers), and virtual social networks play a strong role in the initial assessment and selection of a new agricultural technology (Norton and Alwang, 2020). Adoption is not a single discrete choice decision, instead farmers can decide on how many acres they can adopt. They may also be able to adopt components sequentially. On-farm trials is one way for farmers to learn about the benefits of adoption and adopt gradually.

Behavioral Preferences and Non-Economic Drivers

Socio-psychological characteristics

There is a growing literature going beyond profit or utility maximization as motives for adoption by economic agents to examining the role of socio-psychological factors in explaining the innovation adoption and diffusion process. Pannell et al., (2006) note that adoption occurs when the landholder perceives that the innovation in question will enhance the achievement of their personal goals, that include economic, social and environmental goals. Tey and Brindal, (2012) found that farmer's perception of perceived profitability of using precision agricultural technology and intention to adopt these technologies play an important role in the adoption decision. Various behavioral preferences of farmers, such as their risk-attitudes, environmental consciousness, information awareness have also been shown to affect technology adoption (Prokopy et al., 2019). Socio-psychological factors like perceived response efficacy or a belief that adopting an additional practice makes a difference to environmental quality (Wilson et al., 2014); subjective norms or the perceived social pressure from peers to behave accordingly i.e., farmers' perceived social pressure to apply fertilizer on the basis of soil test results as their neighbors (Zhang et al., 2015); perceived control or the control on extent of adoption and management skill i.e., ability to undertake a practice that has potential for nutrient loss reduction (Doran et al., 2020); and, perceived sources or the degree to which farmers perceive they have access to necessary resources i.e., finance, labor, time, farmer networking, and extension consultant (Daxini et al., 2019), are also important determinants of adoption behavior[4]. Pathak et al., (2019) note that studies analyzing the adoption of precision agricultural technologies have typically not considered the multidimensional and complex nature of the adoption process.

Farm Characteristics

Shang et al. (2021) conducted an extensive review of studies that focused on non-economic determinants of decisions to adopt digital farming technologies[5]. They found a significant effect of farm characteristics, including, biophysical conditions, such as land quality and spatial variability in land quality, and use of complementary technologies (for example, probability of adopting yield mapping technology increases if farmers have already used a VRT (Isgin et al., 2008). Land and livestock ownership also influence technology adoption, particularly if the precision technology requires investment which is attached to the land itself (such as precision irrigation) (Moreno and Sunding, 2005; Fernández Lambert et al., 2015).

Farmer Characteristics

Familiarity of operators with computer use in farm management make them comfortable in using and adopting digital technologies (D'Antoni et al., 2012). Other farmer characteristics like off-farm income and farming experience could influence digital technology adoption. For

[4] These studies analyzed likelihood of adoption of BMPs for reducing nutrient loss and restoring water quality including cover cropping, strip cropping, conservation tillage, soil testing to determine fertilizer requirements, variable rate fertilization application, and recommended dose and timing of fertilizer application.

[5] They provide quantitative impacts wherever possible with statistical significance of several factors under each of the six broad categories i.e., farm characteristics, operator characteristics, interactions, institutions, technological attributes, and psychological factors, on PAT adoption.

example, Schimmelpfennig, (2016) find significant impact of off-farm income on adoption of a bundle of technologies (yield monitor, GPS, and VRT) whereas Asare and Segarra, (2018) find farming experience has a positive impact on georeferenced grid soil sampling technology adoption. Using debt and asset ratio as a measurement of risk preference, Isgin et al., (2008) find that famers with a higher risk bearing capacity tend to adopt more precision agricultural technologies. As novel farming technologies involve more uncertainty than traditional ones, research has highlighted the importance of not only risk aversion (Marra et al., 2003) but also loss aversion and ambiguity aversion (Barham et al., 2014) and subjective view of risk (Liu 2013) in determining their potential adoption.

Technological Attributes

Attributes such as relative advantage (or perceived net benefit), complexity, compatibilty, and trialability are important determinants of digital technology adoption (Adrian et al., 2005). Pannell et al. find that innovations are more likely to be adopted when they have a high 'relative advantage' (perceived superiority to the idea or practice that it supersedes), and when they are readily trialable (easy to test and learn about before adoption). Shang et al., (2021) emphasize the effect of concerns about data safety on digital technology adoption decision since famers are concerned with potential misuse of digitally gathered data by technology service providers. Additionally, adoption can be constrained by the lack of proper user interface leading to difficulty in use, limited access to information and technical assistance (Zhang et al., 2021).

Interaction and Information Source

Access to information about the technology also influences adoption decisions. The effect of extension services, technology providers and equipment providers has been found to have mixed effects depending on farmer belief in usefulness of the information and their trust in it. Weber and McCann, (2015) find that practices to increase N use efficiency i.e., N soil testing, plant tissue testing, and N transformation inhibitors, were less likely to be adopted by farmers receiving no N fertilizer recommendations compared to the ones receiving recommendations from a crop consultant. They also find that N soil testing and plant tissue testing were less likely to be adopted by farmers receiving N recommendations from fertilizer dealers compared to the ones receiving no N fertilizer recommendations which suggests the impact of source of information on adoption.

Effect of Networks and Spillovers

Studies have generally found positive influence of adopters within a social network on acceptance of a novel technology (Bandiera and Rasul, 2006). Information shared by adopters amongst individuals within a social network influences potential adopters to initiate experimentation and proceed further based on gathered experience. At the same time it is found that having many adopters in the network increases incentives to delay adoption strategically and free ride on the knowledge accumulated by others i.e., social effects are positive when there are few adopters in the network, and negative when there are many. Innovation diffusion in agriculture creates both the knowledge (information) and environmental (externality) spillovers which create feedback effects in determining technology adoption in the neighborhood. Even though there are spatial and temporal connectedness among these spillovers, technology diffusion models in agriculture have rarely addressed these impacts for coordinated decisions among farmers (Lewis et al., 2011). Few studies have examined the spatial spillovers in adoption decisions (the effect of technology adoption decision on one's neighbors) or temporal spillover impact (the effect of technology adoption on an individual's likelihood of subsequently adopting other technologies in future (Turinawe et al., 2015; Wollni and Andersson, 2014). Wollni and Andersson (2014) find the likelihood of adopting organic farming increased as a result of information spillover from the neighborhood. Similarly, Turinawe et al. (2015) find that the probability of adoption of soil and water conservation technologies increased if neighbors adopted similar practices.

Other Considerations

Enabling technologies, such as adoption of computers, electronic communication methods and access to high-speed internet are needed to achieve the full utilization of digitally-enabled precision technologies (Khanna, 2020). Monitoring and sensing technologies require computers and GPS-based mapping of yield and soil data, unmanned aerial vehicles or drones, and remote soil sensors that generate real-time data on soil nutrient levels. Auto-steer systems are driven by satellite based guidance systems and paired with telematics, or the real-time data collection for machine and harvesting efficiency management. Information generated by precision technologies can then be transmitted via short-range wireless or WiFi technologies (which are more efficient than a manual transfer of collected data) to cloud-based farm data management systems for further analysis.

Dependable and high-speed internet connectivity are critical for wireless data transfer for uploading and downloading data from the field, for operating auto-steer and VRT and for two-way wireless data transfer between farmers and aggregators. Internet connectivity and access to computers is not yet universal even in the US; only 26% of rural Americans had access to high-speed fixed service in 2017 (LoPiccalo, 2021). Broadband adoption is not homogenous across farms. Larger farms, farms further upstream (e.g., feed suppliers) and those with international operation are more likely to adopt the Internet and engage in e-Commerce. Other factors that contribute to broadband adoption include farmer age and educational achievement, family size, and previous exposure to computers and the Internet.

Farmers purchasing these services need to share their farm data about crop management, input-use, yields and so on, with the precision farming service provider. This creates concerns about data ownership, privacy and confidentiality and these can create a barrier to adoption in the absence of clarity on these issues. Adoption of digital technologies requires trust in the precision technology service providers to protect data and to provide recommendations that will increase profitability of the farm and reduce its riskiness. It also requires farmers to overcome concerns about data privacy and confidentiality. Landowners that adopt digital technologies are also likely to have less control on their farm operations based on their expertise and previous experience on their farm since these technologies require recommendations for farm management from technology providers based on data from multiple sources and farms.

5. Directions for Future Research: Assessing Ex-Ante Determinants of Adoption and Diffusion of Digital Technologies

The sections above described the insights obtained from the technology adoption literature on factors likely to affect the adoption of digital technologies. Much of this literature has conducted farmer surveys to examine the ex-post determinants of their decision to adopt digital technologies for crop production (see reviews in Shang et al., 2021). These studies typically analyze the discrete decision to adopt existing digital technologies based on farm and farmer characteristics, technology characteristics, institutional factors and behavioral factors. Insights provided by these studies can be limited because of their static nature and because technologies evolve and improve rapidly. To understand the likely drivers of adoption of new or evolving digital technologies that are yet to be commercially available or adopted on a large scale, ex-ante analysis is needed. This can be used to examine the determinants of farmer willingness to adopt or willingness to pay for digital technologies that are still under development. Additionally, systems analyses can be used to examine the mechanisms that will lead to diffusion of new digital agricultural technologies in a region consisting of many heterogeneous farmers that interact with each other and with the technology and their environment in a manner that evolves over time. We now briefly discuss the methods for conducting ex-ante analysis of adoption and diffusion decisions.

Methods for Analyzing Ex-Ante Adoption Decisions

Stated preference methods, specifically contingent valuation methods and choice experiments, can be used to determine a farmer's hypothetical willingness to adopt digital technologies. These are useful approaches to examine farmers' heterogeneous preferences for new agricultural technologies that lack market data or are not widely adopted (Blasch et al., 2020). They can be used to analyze the effects of heterogeneity in non-pecuniary factors like farmers' perceptions, attitudes, environmental effects, and technology attributes on likely adoption choices (Khanna, 2020).

Comparative studies have shown that when they are well-designed, stated preference methods reveal preferences and willingness to pay estimates that are incentive compatible (Lusk and Schroeder, 2004). The contingent valuation method requires potential adopters to state their willingness to pay for a technology or their willingness to accept an incentive payment to purchase it (Merino-Castello, 2003). Methods for eliciting this willingness can be through open ended questions about willingness to adopt or pay for a product or referendum-style questions about whether or not a respondent would adopt a technology or pay a pre-set amount for it. Respondents are typically presented with a technology with given attributes. As a result, contingent valuation methods are limited in their ability to elicit information about adoption decisions for complex digital technologies with many choices of features and components. Therefore, they do not allow assessments of the relative importance of multiple attributes in influencing the adoption decision. Moreover, the analysis of respondent's behavior is static (Le Pira et al., 2017).

In contrast choice experiments allow respondents to choose among bundles of technology attributes and related performance outcomes, at pre-specified prices. A choice experiment involves choosing the most preferred option relative to the other options which includes the status quo (Merino-Castello, 2003). Choice experiments mimic actual market behavior where various dimensions of the attributes are considered and provide estimates of willingness to pay for a technology that are consistent with welfare economic theory (Champ et al., 2017). The levels of multiple attributes can be varied across the bundles presented to the respondent and this enables assessment of the willingness to pay estimates associated with individual attributes and assessment of the relative importance of multiple attributes. Moreover, a choice experiment can be designed to account for interaction effects among attributes and estimate the trade-offs that respondents are willing to make between attributes. As such, the willingness to pay estimates from a choice experiment can reveal that potential adopters of a multifunctional digital technology might be willing to pay for two complementary attributes presented together more than they are willing to pay for the sum. Conversely, if potential adopters perceive attributes as substitutes, results from a choice experiment can reveal that they will pay less for a technology that has two attributes presented jointly than for the sum of each one individually.

Limitations of choice experiments include the possibility of strategic behavior, hypothetical bias and cognitive difficulty faced by respondents when examining the complex tradeoff between different sets of attributes. Too many choice attributes will lead to the cognitive difficulty that potential adopters may use decision-shortcuts (heuristics) which do not reflect their preferences (Champ et al., 2017). Focus group meetings can play a vital role by providing information about the attributes that are important to farmers when considering adopting a digital product or service. Focus groups are also important to identify the levels of the attributes that are relevant for farmers. Another limitation of welfare estimates derived from choice experiments is measurement error if attributes and their levels are not presented in accurate, measurable, and interpretable terms (Schultz et al., 2012). For example, describing a technology attribute related to data safety, compatibility, or learning time in a way that is relatable to farmers, scientifically accurate, and measurable by the researcher might be challenging. Despite their advantages, choice experiments are limited in their ability to capture the dynamic nature of preferences and adoption decisions and their ability to be informative about technology diffusion across groups of farmers. However, these limitations can be overcome when choice experiments are dynamically integrated with system-level models, described below.

Agent-Based Models

One of the approaches for going beyond individual farmer-level adoption decisions to modeling adoption and diffusion of new technologies among heterogenous farmers is using agent-based models (ABMs). ABMs can capture system-level outcomes that result from interactions among autonomous heterogenous agents and interactions between each agent and their environment. ABMs differ from standard neoclassical economic models in that agent decisions do not need to be driven by a single objective of maximizing profit or utility nor do they need to be rational, as defined by neoclassical economic theory. Standard economic models analyze static adoption decision but not the process of diffusion through adopter groups, innovators, early adopters, early majority, late majority, and laggards (Rogers, 2010). These models also do not explicitly represent direct interactions among agents, the effects of neighbors' information, or the role for non-economic behavioral and psychological factors like attitudes and subjective norms. With ABMs, researchers can analyze the effects of agent interactions with their neighbors or within their social network and interactions with their environment. As a result, these models can represent how landscape-level outcomes such as adoption and diffusion of new technologies can emerge from agent-level interactions. A review of the literature by Shang et al., (2021) shows that ABMs are yet to be applied to study adoption and diffusion of digital agricultural technologies. The authors also note that current agricultural ABMs applied are not based on empirical farm-level evidence. Huber et al., (2018) also note the need for future agent-based models to incorporate empirical data on farm or farmers' characteristics and farmers' heterogeneous preferences.

There are at least three promising ways to integrating evidence from farm choice exoeriment surveys in ABMs of ex-ante farmer adoption of digital technologies. In the first, the econometric models used to analyze choice data can be used to specify the probability that farmer-agents adopt a technology (e.g., Gatta et al., 2020). In the second, the econometric model parameter estimates can be used to specify the utility of agents adopting a technology (Le Pira et al., 2017). In the third, the welfare estimates from the choice experiment results can be used to compare the WTP of each farmers-agent with the cost of the technology so that adoption takes place when WTP exceeds costs. In order to model the effect of agent heterogeneity on adoption, researchers can include interaction effects of the status quo variable or the price variable with individual characteristics (e.g., Huang et al., 2007) or environmental variables, or use latent class models to identify heterogeneous groups of agents from surveys (Holm et al., 2016). The agent decision criterion – the probability, the utility, or the WTP – can be explicitly modeled as a function of fixed and dynamic individual characteristics, environmental variables, and behavior of other agents. As such, the decision to adopt can take into account agent heterogeneity and be dynamically updated as a function of changing socio-ecological determinants such as the action of neighbors and the stock of a biological organism relevant to the technology (e.g., weeds). Together, individual decisions to adopt and their connectedness of agents either socially or through environmental factors, lead to system-level outcomes such as technology diffusion and economic and environmental outcomes that could not be represented using standard economic models alone.

6. Conclusions

This paper examines the imperative for digital technologies to enhance the economic and environmental sustainability of agriculture in the US. We discuss ways in which these technologies can increase effectiveness and lower labor costs of site-specific management of crops, weed control and improvements in soil health. The capabilities of digital technologies are developing rapidly and their costs are expected to decline in the future. These technologies have The existing literature has examined the drivers of adoption of new technologies by farmers and of earlier generations of precision technologies. This literature shows that adoption of these technologies will depend on both economic and behavioral drivers as well as on policy incentives that reward farmers for providing ecosystem services. While it provides insights that are applicable to the emerging digital technologies, future research is needed to examine ex-ante willingness to adopt these emerging technologies that may differ considerably from existing precision technologies. Choice experiments provide an appropriate approach to examine the technology attributes and performance features and behavioral factors that are likely to induce adoption and the trade-offs farmers are willing to make among these features. These can be combined with ABMs to go beyond individual farmer-level adoption decisions to modeling adoption and diffusion of new technologies among heterogenous farmers in a region.

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