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Precision Agriculture: Trends, Issues, and Application to Production in the U.S.

By Scott W. Fausti

The theme of the Fall 2021 issue of the Western Economics Forum (WEF) is “Precision Agriculture: Trends, Issues, and Application in the U.S.” This special issue focuses on precision agriculture (PA) tools and strategies that contribute economic benefit to agricultural and community value chains in the Midwest and Western regions of the United States.

Comprised of seven articles, this special issue is divided into three broad categories: a) Data analysis and its implications for incorporating PA into a producer’s management strategy, b) Economic implications of PA adoption on a producer’s farm management strategy, and c) The role of the retail PA custom service industry in facilitating the producer’s PA adoption decision.

Beginning with three articles on PA data and data analysis, Luck and Thompson open the data analysis discussion by providing producers a guide to developing on-farm field trials to identify in-field soil variability in order to determine the appropriate PA management strategy for row crops. Next, DeLay et al. examine the rate of adoption of PA data collection software by corn and soybean producers in the U.S. Wrapping up the data analysis section, Wang and Wood discuss the application of PA cropping strategies for tree nuts (pecan orchards).

The next section includes a pair of articles examining issues associated with the rate of PA adoption. Kolady and Van der Sluis examine the relationship between a producer’s adoption of a PA management strategy and the producer’s decision to engage in conservation practices on their farm. DeLay and Comstock investigate the relationship between the number of PA technologies adopted by a corn producer and the scale economies of the producer’s farming operation using national data.

The retail custom PA services industry and its role in the producer’s PA adoption decision are discussed in the final two articles included in the themed portion of this issue. First, Fausti et al. discuss the PA literature’s view of the role of custom services in overcoming the PA adoption barriers of management complexity, and the financial cost barriers of adopting a PA-based management strategy for crop production. In the second article, Fausti et al. focus on the lack of PA workforce development as a constraint on the custom service industry’s ability to expand PA services to agriculture producers.

The final article appearing in this WEF special issue is independent of the special issue theme, discussing the development and current status of the cannabis industry in the U.S.

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Adding Value to Farm Data by Leveraging Precision Agriculture Technologies for On-Farm Research

By Joe Luck¹ and Laura J. Thompson²

Abstract
Many farmers have invested heavily in precision agriculture technologies (e.g., variable rate planters and nutrient application systems) and continually seek ways to gain value from those systems. Coupling these tools with farm management information systems (FMIS) software to deploy and analyze on-farm research can help fill that void and allow farmers to optimize their crop inputs or possibly assess new services for input management. This article will discuss methods for successfully deploying such studies using precision agriculture technologies with specific emphasis on considerations related to design, data collection and analyses of trial data.

Keywords: statistics, variable rate technologies, digital agriculture, marginal net return

Introduction
Over the past decade it has become clear to many in the agricultural profession that there is unquestionable value in the precision agriculture datasets (e.g., yield maps, as-applied datasets, georeferenced soil samples, imagery, etc.) that farmers are collecting. What remains unclear is how farmers can benefit from these datasets collected as they conduct their typical field operations. Not everyone has time to become an expert in field research, data science or analytics. However, many leading industry groups have excelled at just that in the past few years.

Many farmers in the Corn Belt have invested heavily (possibly from high commodity prices from 2008 to 2013) in variable rate technologies for planting and nutrient applications. Producers continue to seek guidance on how to make such systems pay back in their operations. Engaging with farmers via on-farm research projects has allowed researchers and extension professionals to utilize these existing technologies to deploy field studies and gather actionable information about their operations. There are several aspects of on-farm research which cannot be ignored as we seek to utilize precision agriculture technologies. There have also been a few barriers keeping farmers from engaging in their own research projects. Time required to design and deploy field trials (problematic due to manually planning, flagging and plotting field trial locations) and analyzing and interpreting trial results have typically been among the top reasons farmers do not engage in conducting field trials. Again, not everyone has a deep skillset in data science, and the statistical analyses to ensure that field study results are interpreted appropriately are critical for making the right decisions.

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Importance of Field Trial Design

When starting this process, there are a few key components of trial design that must be considered for getting good results. Isolating specific treatments is key, for example, if a nitrogen (N) rate study is the focus, to ensure that blended products are not used which could confound the study results. For instance, 28-0-0-5 has a small portion of sulfur, that may or may not affect the results; but those effects cannot be separated from the overall results. A 28% liquid urea-ammonium nitrate (UAN) solution would be preferred to test N rate effects on yield. When product studies are being considered, leaving a check or ‘no application’ as a treatment is necessary. For example, if a producer were curious whether a fungicide application around the R3 growth stage in soybeans would boost yields, mixing in untreated strips would allow for that direct comparison. Once treatments are finalized, plot layout and organization are the next steps in the process. All treatments are organized into blocks or replications (Reps) as you can see in Figure 1. Each block (or Rep) contains all three treatments in this example, note the check or ‘no product’ strip as well. For rate studies, the check treatment might be the farmer’s typical rate. The final design element to mention is randomization. Notice that the order at which each treatment occurs in Figure 1 changes as you go from Rep 1 to Rep 4. Randomly alternating this order helps reduce the potential impact of natural variability within a field. For example, in a field where yield steadily increased moving from east to west, we would bias our results based on the order we selected for treatments if we did not use randomization.

Figure 1: Trial Design Incorporating Replication of Treatments and Randomization of Treatment Order for Multi-product Testing (Nebraska Extension, 2013).

Consequences of Poor Study Design-A Variable Rate Seeding Case Study

The benefits and consequences of good study design can be illustrated best by reviewing the results of a recent on-farm research study. In this example, a variable rate planter was used to deploy a seeding rate study; the goal was to help the farmer determine the optimal seeding rate for this field.
A variable rate prescription map was created for three seeding target rates: 32 ksds/ac, 36 ksds/ac (grower’s typical rate), and 40 ksds/ac (Figure 2). Note that the three treatments are organized into each of the six blocks and the treatment order is randomized within each block. A typical recommendation is a minimum of six blocks or replications for a field study, but three should be used as an absolute minimum.

**Figure 2: Variable Rate Corn Seeding Prescription Map (With Corresponding Target Rates) for Deploying On-farm Research Study**

Often study participants ask: Why spend so much time with multiple replications and randomization for studies? We can observe the results which are shown in Figure 3. Marginal net return (MNR) was calculated for each treatment as shown in equation 1. Note that in four of six blocks (circled in red), the lowest seeding rate resulted in the highest MNR, on average, MNR was $707, $695, and $680 for the 32 ksds/ac, 36 ksds/ac, and 40 ksds/ac seeding rates, respectively.

\[
\text{MNR ($/ac) = \text{Yield (bu/ac) \times \text{Price ($/bu) – Seed Rate (ksds/ac) \times Price ($/ksds)}} \quad \text{Eqn 1.}
\]

From the statistical analysis of this field trial, we were able to conclude that the MNR values calculated for each treatment (seeding rates) were statistically significant, thus we could show improved profitability for that field site had the producer used the lowest seeding rate. In the future, the farmer might take advantage of this information and increase on-farm profitability by $12/ac based on these data.

What is the potential consequence if the field trial did not follow the design protocols? We can look at two potential scenarios shown in Figure 4. Scenario A in Figure 4 illustrates the layout if we had, by chance, placed blocks 3 and 5 out in the field. All three treatments are represented, and the treatment order is randomized within each block. However, without additional replications, we would not be able to perform a statistical analysis and we would have learned that the 36 ksds/ac seeding rate would have been most profitable. Reviewing the full-field dataset MNR results (Figure 3), this could cost the grower $12/ac.
Often times, field trials may be developed with only a single plot of a proposed treatment placed in a field with the farmer’s current practice surrounding that plot (Figure 4, Scenario B). What is the consequence of Scenario B in Figure 4 where a higher rate (40 ksds/ac) was placed within the typical grower rate? Again, reviewing the full-field MNR dataset, this would potentially cost us $15/ac versus the current grower practice. If the producer were to adopt the 32 ksds/ac rate, this scenario could cost $27/ac versus the optimal practice. Since Scenario B contains no replications of the evaluation, statistical analysis could not be performed and we would not be able to conclude that this higher seeding rate really contributed to higher MNR, it could have been due to natural variability.
Additional Considerations for Field Trial Activities using Precision Ag Technologies

There are some additional considerations when using precision agriculture technologies to deploy field studies which offer some benefits and challenges to the process. For instance, differences between treatments for rate studies need to be large enough such that we know the field equipment can manage the specified rates effectively. For soybeans, we would typically want 30 to 40 ksd/ac difference between each treatment. For corn seeding rate studies, 4 ksd/ac is preferred between treatments and with N rate studies, a minimum of 30 lb N/ac is recommended between treatments. As we move from field-length strips to prescription maps for sub-field plot areas, we need to expect some delay in rate changes from the equipment, which will affect our minimum plot lengths. An additional factor to consider when determining minimum plot lengths is the limitations of a yield monitor system for data collection. Previous research has indicated that yield monitors need to collect somewhere between 200 to 250 feet of data to correlate well with a weigh wagon (Al-Mhasneh and Colvin, 2000). A recent field study at Iowa State University confirmed that for field plots less than 200 feet, the yield data collected was unable to distinguish among treatments using N as a test variable (Bergman et al., 2021). Our team recommends designing plots to be 300 feet in length, which allows enough distance for application equipment to transition and provides enough remaining yield data points after yield monitor flow delay is considered.

Figure 5 illustrates how a variable rate prescription map can be used to deploy a field study, in this case for soybean seeding rates. Treatment plots were designed to be 300 feet in length, in this particular case, the combine header width was 35 feet and plot widths were designed at 90 feet (three planter passes at 30 feet per pass). Sixteen total blocks were designed into this particular study and the prescription map was uploaded to the planter monitor. Note that from the as-applied planter data that the prescription was not enabled in the southeast corner of the study for several passes. You may also note from the as-applied data that in many instances the delay in rate changes as the planter passed between individual treatment plots was considerable. Checking as-applied data is a critical step in the study assessment to ensure that equipment achieved desired target rates throughout the study area. We did not anticipate the farmer planting the field study shown in Figure 5 at an angle; we had anticipated east-west passes and designed the plot dimensions accordingly. Because as-applied data were collected, we were able to eliminate portions of the study in the southeast field areas where rate changes did not occur. In addition, we were able to isolate where sufficient strips of yield monitor data (greater than 200 feet) could be extracted from areas corresponding to where the planter achieved target seeding rates. Due to the datasets collected, we were able to distinguish eight blocks of good data that could be used to estimate MNR and verify results using statistical analyses and the study did not have to be discarded. The results showed the farmer could reduce seeding rates (from their typical 150 ksd/ac) while increasing potential profitability by 25 to 40 $/ac. Due to the high number of Reps (eight), statistical analyses detected significant differences in yield from the seeding rate treatments down to 3 bu/ac.
Importance of Quality Data Collection Using Yield Monitoring Systems

Successful completion of field trials using yield monitors for data collection requires a few key steps to ensure quality data are being used. First, the yield monitor must be calibrated accurately according to the manufacturers’ specifications. This typically involved collecting four to six small calibration loads (60 to 90 bu each) representing varying grain flow conditions through the harvester (Luck and Fulton, 2014). Each of those loads should be weighed using a grain cart with scales and those weights are entered into the yield monitor; this allows the yield monitor to generate a calibration curve for estimated mass flow (lb./sec) of grain through the machine. In an ideal situation, that calibration would occur immediately prior to harvesting the field study under similar crop conditions (within the same field, if possible). The operator can also improve data quality by minimizing speed changes while harvesting within the study area. The distance traveled by the machine between yield monitor data points (typically logged every second) is used to estimate the harvest area for that short interval. Acceleration and deceleration will inevitably cause some error in that estimate, so constant speed is critical to obtaining high quality yield data. Once the yield data are downloaded, visual inspection of the data should be performed to note any outliers which may exist, or software may be used to perform this quality check. We recommend Yield Editor software (freely available from the USDA) as a post-processing check on all yield data collected during on-farm research studies (USDA, 2021). Errors in data recording can always occur and lead to extremely high or low yield data points within plot areas. Often times, we can attribute that to some machine operating parameter like travel speed, for instance when the operator decelerates quickly, yield data are likely to be inflated to unrealistic values (Sudduth et al., 2012; Luck et al., 2015).

Yield data quality can have an impact on study results. Recall the corn seeding rate example shown in Figure 2; in this study the field length strips were approximately 600 feet long. As the harvester entered into each strip, it took a few seconds for the machine to develop a full grain flow (i.e., lag time), at the beginning of each strip. This situation resulted in lower yield data estimates, and the recommendation would be to remove those points via plot buffers or software like Yield
Editor. Had those points remained in the analysis, we would not have been able to statistically differentiate between the MNR values for the two lower seeding rates. Using post-processing (i.e., cleaning) techniques for removing yield data points, the statistical analysis indicated that the lowest seeding rate was indeed more profitable than the farmer’s standard rate by $12/ac (Table 1).

Table 1: Example of Potential Differences in Study Results Due to Yield Data Quality Issues (Different Letters Indicated Significant Differences at Alpha = 0.1)

<table>
<thead>
<tr>
<th>Target Seed Pop</th>
<th>Raw Yield Data</th>
<th>Clean Yield Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>32K</td>
<td>237</td>
<td>27</td>
</tr>
<tr>
<td>36K</td>
<td>242</td>
<td>30</td>
</tr>
<tr>
<td>40K</td>
<td>239</td>
<td>34</td>
</tr>
</tbody>
</table>

While several steps in this process requires some special skills, farm management information systems are becoming more user-friendly as those software providers further develop their tools. Some software systems now include planning and analysis tools for on-farm research experiments and allow the user to quickly design field trials to be deployed using their variable rate equipment. The University of Nebraska-Lincoln has a long history of working with producers via our On-Farm Research Network (https://cropwatch.unl.edu/on-farm-research) and there are several great resources on how to get started down that road. We note a lot of industry partners that are working with their cooperating producers to carry out well-designed on-farm research studies as well. In other cases, we have seen studies were clearly not designed to deliver reliable data to support on-farm decisions. One of our goals is to help producers with access to precision agriculture technologies take advantage of these tools on an annual basis to collect the data necessary to optimize their crop inputs. In addition, similar techniques may be used to help farmers evaluate commercially available crop input decision services that are provided to them.

Summary

Using precision agriculture tools and technologies to conduct on-farm research is another opportunity for producers to get some return on investment in these systems. When conducting these field studies, critical steps include appropriate trial design, validation of trial deployment, accurate data collection and statistical analysis. Failing to consider just one of these aspects, as demonstrated in this article, could lead to inaccurate results and potential costly decisions at the farm level. However, well implemented on-farm research studies using precision agriculture technologies can lead to informed, data-driven decisions regarding management impacts on crop performance and profitability.
References


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Farm Data Collection and Software Adoption in Commercial Scale U.S. Corn-Soybean Farms

By Nathan DeLay1, James Mintert2, and Nathanael Thompson3

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Abstract
A survey of 800 commercial scale corn and soybean operations was conducted to examine farm data collection and analysis practices among large farms. Results indicated that collection of data from yield monitors, soil samples, and aerial imagery were common, but varied depending on farm size and operator characteristics. Over 40% of commercial scale farms which collect data use at least one ag-data technology software. Farms that use ag data software are larger, have younger operators, and higher levels of educational attainment. The majority of software adopters use more than one software product, highlighting the importance of inter-operability in ag-tech.

Keywords: farm data, precision agriculture, technology adoption

Background
Digital agriculture appears to be exploding in terms of the number of firms providing digital agriculture tools and software as well as the investment dollars the sector is attracting. Large agribusiness firms have made major investments including Monsanto’s (now Bayer) purchase of The Climate Corporation in 2013 and, more recently, AGCO’s purchase of Precision Planting and DuPont’s (now Corteva) purchase of Granular, both in 2017. Despite the sector’s growth, there is a paucity of information available regarding factors that influence today’s farming operations’ adoption of digital agriculture technology to make decisions and, possibly, improve farm productivity.

To learn more about how U.S. commercial scale corn and soybean farms are actually gathering and using data on their farms, a telephone survey of U.S. commercial corn and soybean producers was conducted from August 5 to August 30, 2019 (Purdue University Institutional Review Board approval #1906022382). Previous research confirmed that larger scale farming operations are more likely to use various precision agriculture technologies (Daberkow and McBride, 2003; Fernandez-
Cornejo et al., 2001; Roberts et al., 2004; Schimmelpfennig, 2016). Since the survey’s purpose was to learn more about the key factors influencing adoption and use of digital agriculture technologies, rather than simply the adoption rate of various technologies, the survey intentionally targeted commercial scale farms that are most likely to use digital technology.

Commercial scale farms for the purpose of this study are defined as having farmland of 1,000 acres or more with a corn and/or soybean enterprise as part of the farming operation. However, USDA-NASS (2020) data indicates that over half of the farms with more than 1,000 acres of farmland actually operate less than 2,000 acres. To ensure that survey responses were representative of truly larger-scale farms as well as mid-size farms, the survey was designed to ensure that half of the responses were from farms operating between 1,000 and 1,999 acres and half of the responses were from farms operating 2,000 acres or more. The final sample included 400 respondents farming 1,000 to 1,999 acres and 400 respondents operating 2,000 acres or more of farmland.

The advantage of a phone survey is that researchers can keep calling until enough responses are gathered to meet sampling targets and generate reliable results. The disadvantage of a phone survey is it needs to be short and relatively easy to respond to, or else respondents are unlikely to complete the survey. With that thought in mind, the survey design focused on three types of data: yield monitor data, grid or zone soil sample data, and aerial or satellite imagery data to learn more about the factors influencing agriculture data software adoption and management practices.

**Farm Characteristics and Data Collection Practices**

Table 1 displays summary statistics of the sample’s farm and operator characteristics. Eighty percent of all survey respondents were over age 50 and just over one-third (35%) were over the age of 65, which compares to NASS’ estimate that the average age of U.S. farmers is 59. Forty percent of survey respondents had a bachelor’s degree and an additional 30% of respondents attended college.

Table 2 summarizes precision agriculture adoption and data analysis practices of sampled farms. Usage of well-established precision agriculture technologies was high as 92% of respondents reported using GPS guidance/autosteer technology while 71% and 59% said they used variable rate fertilizer and variable rate seeding, respectively. Unmanned aerial vehicle (UAV) (i.e., drone) usage among respondents was much lower than the other technologies as just over one-fourth (26%) of respondents reported using a UAV. Eighty percent of respondents reported having high-speed internet access and just over two-fifths of survey respondents reported using Microsoft Excel (43%) and/or a farm data software application (44%) to analyze farm data. While guidance technology usage among our sample was comparable to representative estimates for similar size classes (e.g., USDA Agricultural Resource Management Survey (ARMS)), use of variable rate technology (VRT), UAVs, and software were far higher, suggesting our sample is more advanced relative to the general population of commercial farms in terms of precision agriculture adoption.

Farm data collection among commercial scale corn and soybean farm operations in the survey sample was also quite high. Table 2 reports the proportion of farms collecting each of the three data types targeted on the survey: yield monitor, grid or zone soil samples, and aerial or satellite imagery data. Ninety-three percent of survey respondents collected at least one form of farm data. However, 7% of these commercial scale survey respondents reported not collecting any of the three data types and, furthermore, few members of that group indicate it is “very likely” that they would begin collecting data in the future. To date, farms that choose not to collect data are referred to as Non-
Data Collectors (NDCs). Farms collecting one or more of the three data types are referred to as Data Collectors (DCs).

Data Collector vs. Non-Data Collector Farms
Although a majority of NDCs used GPS guidance/autosteer on their farms, the percentage was lower (73%) than among DC farms (93%). DCs were also much more likely to use variable rate fertilizer (74% of farms) than NDCs (27% of farms) and nearly three times as likely to use variable rate seeding (62% of farms) as NDCs (22% of farms). DC farms were four times as likely to use a UAV (28%) as NDCs (7%). When it comes to software usage, there were also big differences between DCs and NDCs. Fourteen percent of NDCs reported using spreadsheets (Microsoft Excel) while just 5% of NDCs used a farm data software package. This stands in sharp contrast to DCs, 45% of whom reported using spreadsheets and 47% reported using at least one type of farm data software package for analysis. Given the notable association between the collection of farm data and use of farm data software, the characteristics of software adopters and the types of products they use is examined further.

Ag-data Software Adoption
Overall, 47% of DCs used at least one ag-data software product, but adoption varied by farm size. Sixty-three percent of farms with 5,000 acres or more used one or more software products vs. 36% of farms with between 1,000 and 2,000 acres of cropland. Software adoption was also related to operator age and farm educational attainment. Figure 1 shows that for operators over the age of 65, those with some college were almost twice as likely to use farm data software as those with a high school diploma. A similar pattern emerges for operators aged 51-65, but in their case, the largest difference in adoption was between those with and without a bachelor’s degree or higher. Usage of software platforms was common among young operators of all levels of education, but adoption rises sharply for farmers with a post-graduate degree (Master’s or Ph.D.). These differences in ag-data software usage by age group may reflect the way educational attainment has changed as a signifier of specialization over time.

Respondents that used at least one type of ag-data software were asked to identify which specific platforms they use. Figure 2 shows the proportion of data software subscribers that used each of eight popular software products. Over half of software adopters used Climate FieldView, a Bayer acquisition, while 44% used John Deere’s Operations Center, and 22% subscribed to Case IH’s AFS platform. Usage of Operations Center and AFS were generally in line with their respective market shares for farm equipment. Just behind AFS was Trimble at 21% of software subscribers, and Farmers Business Network (FBN) at 19%. Encirca (owned by Corteva) was used by 14% of software users while Granular (also Corteva) was at 9%. Note that, after the survey was conducted, Encirca was integrated into the Granular platform. FarmersEdge, headquartered in Winnipeg, MB, was used by 10% of software adopters. Interestingly, 24% of software users subscribed to a product not included in our survey. This implies a long tail in the farm data software market. Note that reported percentages represent usage among commercial corn and soybean operations that over-index for precision farming practices and, as a result, should not be interpreted as true market shares in the farm data software sector.
There was significant variation in product offerings across software platforms. John Deere Operations Center and Case IH AFS collect telematics and input application data from farm equipment but are capable of integrating other systems. FBN provides benchmarking input cost intelligence to its subscribers in the form of a “club good”—data within the FBN network is non-rival but access to the network is excludable. Other platforms such as FieldView and FarmersEdge provide agronomic insights to improve decision-making. Granular offers solutions for work-flow management. Most platforms offer multiple, sometimes overlapping, solutions making them difficult to classify easily. This may explain survey respondents’ propensity to adopt multiple software products. Figure 3 shows that the vast majority of software subscribers in our sample (70%) used more than one product and the average software-adopting farm used between two and three products.

Though we did not ask the order in which farms adopted various technologies, we can get a sense of this by looking at the types of software used by farms that adopt multiple products. Figure 4 shows the types of platforms used by farms that adopted a single product and those that had two or more products. Of farms that used more than one type of ag-data software, nearly 70% used Climate FieldView and 53% used John Deere Operations Center. But among those that used only one software product, FieldView came in at less than 19% while Operations Center made up 28%, making Operations Center the most popular product among single-platform users. These patterns imply that ag-data software products are adopted sequentially based on their complementary offerings. Each platform delivers farm data services that meet the needs of farms at different stages of the farm data pipeline. For example, John Deere Operations Center is primarily a data generation and transfer platform that integrates with multiple other ag-data products. Layering it with Climate FieldView—with its data analysis and prescription capabilities—represents the logical next step in data value discovery.

Conclusions
Farm data collection and use is very high among commercial scale corn and soybean farms. Ninety-three percent of the 800 farms surveyed, referred to as DCs, reported collecting at least one of three major data types: yield data, grid or zone sample data, and aerial or satellite imagery data. Comparing the small percentage of NDCs to DCs reveals that DCs were much more likely to use computer software in the management of their farms and to use a UAV. DCs were also more likely to use precision agriculture technologies such as variable rate seeding and variable rate fertilizer applications than NDCs.

We find that farm data software is popular among commercial scale farms in our sample. Over 40% used at least one software platform and among users, most (70%) subscribed to more than one product. Software adoption was related to farm and operator characteristics (farm size, operator age, and educational attainment). Notably, the relationship between education and software usage depends on operator age, signifying changes in educational attainment over time. It also suggests that the profile of “advanced” farmers may be changing.

The widespread practice of using more than one software product highlights the importance of inter-operability in precision farming and data usage. The types of software used together and individually suggests that farms adopt data generation and transfer systems such as John Deere Operations Center first, which they later integrate with software that provides prescriptive service
The on-farm benefits that flow from data collection and use likely depend on how well these different tools communicate with one another.

References


Figure 1. Farm Data Software Adoption by Age and Education

- Post-Graduate Degree
- Bachelor’s Degree
- Some College
- High School Degree

Figure 2. Farm Data Software Products Used by Software Users

- Climate FieldView: 52%
- John Deere Operations Center: 44%
- Case IH AFS Software: 22%
- Trimble: 21%
- FBN: 19%
- Encirca: 14%
- FarmersEdge: 10%
- Granular: 9%
- Other: 24%
Figure 3. Number of Software Products Used by Farm Data Software Adopters

Figure 4. Farm Data Software Products by Number of Products Adopted
Table 1. Farm & Operator Demographics<sup>a</sup>

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<thead>
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<th>Farm size (total acres operated)</th>
<th>% of Survey Respondents</th>
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<td>1,000-1,999 acres</td>
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<td>2,000-4,999 acres</td>
<td>36%</td>
</tr>
<tr>
<td>5,000+ acres</td>
<td>15%</td>
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<tr>
<th>Farm owner/operator age</th>
<th>% of Survey Respondents</th>
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<td>&lt;35 years</td>
<td>2%</td>
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<th>Farm educational attainment&lt;sup&gt;b&lt;/sup&gt;</th>
<th>% of Survey Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>High school diploma</td>
<td>21%</td>
</tr>
<tr>
<td>Some college</td>
<td>30%</td>
</tr>
<tr>
<td>Bachelor's degree</td>
<td>40%</td>
</tr>
<tr>
<td>Post-graduate degree</td>
<td>9%</td>
</tr>
</tbody>
</table>

Notes: <sup>a</sup> Survey sample includes 800 corn and soybean farms with 1,000 acres or more in operation. <sup>b</sup> Highest level of educational attainment among all full-time employees of the farm, including owner/operators.

Table 2. Precision Agriculture Adoption, Data Collection, and Sharing<sup>c</sup>

<table>
<thead>
<tr>
<th>Precision agriculture adoption</th>
<th>% of Survey Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-speed internet access</td>
<td>80%</td>
</tr>
<tr>
<td>GPS guidance/autosteer</td>
<td>92%</td>
</tr>
<tr>
<td>Variable rate seed application</td>
<td>59%</td>
</tr>
<tr>
<td>Variable rate fertilizer application</td>
<td>71%</td>
</tr>
<tr>
<td>UAV</td>
<td>26%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Farm data collection</th>
<th>% of Survey Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield monitor data</td>
<td>82%</td>
</tr>
<tr>
<td>Soil sample data</td>
<td>77%</td>
</tr>
<tr>
<td>UAV/SAT data</td>
<td>47%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Farm data analysis</th>
<th>% of Survey Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spreadsheets (Microsoft Excel)</td>
<td>82%</td>
</tr>
<tr>
<td>Farm data software</td>
<td>77%</td>
</tr>
<tr>
<td>Designated data employee</td>
<td>47%</td>
</tr>
</tbody>
</table>

Notes: <sup>c</sup> Survey sample includes 800 corn and soybean farms with 1,000 acres or more in operation.
The Application of Precision Agriculture Technologies in US Pecan Production: Challenges and Opportunities

By Haoying Wang¹ and Emily Wood²

Abstract
Precision Agriculture (PA) technologies offer farmers in the US and globally the potential to improve productivity, and provide efficient solutions to a sustainable agro-environmental system. This paper reviews the application of PA technologies in the context of pecan production but with widely applicable insights and suggestions. The review integrates a technological perspective and an economics perspective. Our discussion focuses on challenges and opportunities in key areas of PA technologies, including remote and short-range sensing, wireless sensor networks, variable rate application, yield monitoring, data analytics, cybersecurity, as well as engaging and increasing technology adoption among small and medium-sized farms.

Keywords: Precision Agriculture; Smart Agriculture; Pecans; Tree Crop.

JEL Codes: Q1, O3

Introduction
The concept of PA is not something new. Before mechanized agriculture, smallholder farmers worked small plots with dedicated input and output management. Essentially, their practices were PA on a smaller scale, usually from a few dozens to a few thousands of square meters of land. Such small-scale PA relies solely on human intelligence. Until today, many regions in developing countries still depend on such ancient practices to maximize land productivity. It is the ‘scale up’ that makes a difference between traditional PA and modern PA (Figure 1). In the age of mechanized agriculture, machines and industrial processes have revolutionized the practice of precision management – the birth of whole-field management on a large scale. As information technologies start refining the production management scale, modern farming that integrates human intelligence and artificial intelligence becomes possible – precision management at large scales (e.g., spatial and temporal scales). Shannon et al. (2018) defines modern PA as the agricultural practice based on the use of information and science-rooted decision tools to improve productivity and profitability. Computerized machines (and real-time variable rate applications), high-resolution sensing technologies, and data analytics have enabled farmers to implement PA at a scale of hundreds and thousands of acres.

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Meanwhile, the goal of PA has also diversified. In traditional smallholder PA, the only goal beyond the joy of working on the land is to increase productivity. In modern PA, the goal becomes improving profitability while reducing the environmental impact of agricultural production (Bongiovanni and Lowenberg-DeBoer, 2004). In part, it is due to the growing environmental regulations. More importantly, it is a way to manage the agro-environmental system for long-term economic sustainability. Understanding the diversified goal of PA provides a context for harnessing the development of PA technologies. When it comes to the application of PA technology, as Shannon et al. (2018) emphasized, the required management tools and decision-making processes are as important as the technology itself.

The Journal of Agricultural Science started publishing research related to PA in the 1920s (e.g., Eden and Maskell, 1928). The economics and management literature related to PA did not become active until the 1990s (e.g., Lowenberg-DeBoer and Boehlje, 1996). The development of PA applications reviewed in the literature has focused on field crops, especially commercial row crops like corn and soybeans. Perennial crops like tree nuts and fruits have received less attention despite the potential of PA technologies to improve the management efficiency of these high-value crops. The development in technologies like remote sensing and IoT (Internet of Things) has made it possible for PA research and technologies to progress in the past three decades. A recent review by Bhakta et al. (2019) categorizes PA technologies into three broad areas: data collection, data analysis & decision making, and variable rate control. They can be further categorized into specific technologies. For example, data collection technologies include global positioning systems, remote sensing, wireless sensors, and yield monitors. When it comes to perennial crops, certain technologies play a larger role than others (e.g., unmanned aerial systems and wireless sensors). This is because the crop or tree layout is fixed, which gives an advantage to certain technologies (e.g., soil and water sensors that use stationary loggers). Meanwhile, it requires technologies to have flexible spatial positioning (e.g., yield monitoring and fruit quality detection in three-dimension), which adds new challenges for technologies like yield monitoring and variable rate control (Tu et al., 2020).

This review focuses on the application of PA technologies in tree nuts production, specifically pecan production. Pecan production, compared to other major tree nut crops, is more widely grown in the US. Large pecan orchards can be found from the South to the Southwest. According to the USDA, the bearing acreage of pecans in the US was over 400,000 acres in 2018 (USDA, 2020).
following sections, we first review current PA practices in major pecan-producing states. We then discuss challenges in technology application and future opportunities.

**Precision Agriculture Practice in Pecan-Producing States**

According to recent USDA estimates, US pecan production is a 500-million-dollar industry (USDA, 2020). The major producing states include Arizona (AZ), Georgia (GA), New Mexico (NM), Oklahoma (OK), and Texas (TX). Sizeable operations can also be found in Alabama (AL), California (CA), and Louisiana (LA). Figure 2 presents pecan bearing acreages and yields for all eight states in 2018. There is a considerable yield variation across states. The southwestern and western states have significantly higher yields than the southern states, mainly due to their favorable growing conditions. The application of PA technologies also varies across states due to heterogeneous environmental conditions. The brief review presented in this section is based on data and information available through public domains, including peer-reviewed literature, reports from university extension services, and relevant websites.

In general, the application of PA technologies in pecan production has been slow-moving compared to field crops. Most reported applications focus on irrigation, soil mediation, fertilization, and disease & pest control. Weckler et al. (2015) presented a recent survey of PA technologies used for enhancing pecan production. For example, a real-time wireless sensor network for pecan weevil (*Curculio caryae*) monitoring has been developed. The weevil is a primary pest in pecan production. Among the five major producing states (AZ, GA, NM, OK, TX), several key areas of PA application include (1) smart irrigation implemented through an automated micro-sprinkler system with soil moisture sensors; (2) soil mediation and amendments using variable rate application tools, usually integrated with fertilization management. One of the main goals is to balance soil drainage and water holding capacity. (3) Satellite imageries, drone-based multispectral sensing, and GPS-guided sampling, which are commonly used in assessing field crops, are also being increasingly used for pecan yield monitoring. They also apply to crop load management, which is critical for maximizing

![Figure 2. Pecan Bearing Acreage and Yield in Major Producing States (2018)](image)

3 Since 2019, the USDA has discontinued data reporting for pecan production in Alabama, California, and Louisiana.
pecan yield. (4) Disease & pest control using drone-based multispectral sensing and wireless sensor networks. Satellite imageries tend to be less valuable in this area due to their low resolution. (5) In the Southwest (i.e., AZ and NM), sunlight intake management is also critical. A tree-pruning technology is usually implemented with instruments attached to a GPS-guided ATV or tractor. In the southern states (e.g., AL and LA), properly pruning pecan trees can also make orchards more resistant to natural disasters like heavy storms and hurricanes. Additionally, variable rate technologies may be used for nitrogen application and foliar zinc spray. Both fertilizers are essential for pecan tree growth and nut production. In the case of tree nuts, frequently, the application (e.g., of zinc) needs to be managed in three-dimension, which is still a challenge, as discussed in the following section.

**Precision Agriculture Challenges in Pecan Production**

Pecan production is heterogeneous across states and regions. For instance, disease & pest control is a major challenge for pecan producers in Georgia. In New Mexico, while pecan farms are less concerned about disease and pest issues, irrigation water scarcity and salinity issues are the main regional challenges. Even within the same state, the operation size varies significantly. For example, there are about 2,000 pecan farms in New Mexico. The largest few pecan farms are 3,000-5,000 acres in size. However, many smaller operations are just a few acres. The large variation in operation size has implications for pecan production from both a technological perspective and an organizational perspective. From a technological perspective, it is necessary to note that most PA technologies have been developed and commercialized for field crops. In this context, PA is usually defined by the underlying technologies (Shannon et al., 2018). Hence, the challenges faced by pecan farms often relate to the application of technologies.

First, PA is about understanding and managing the variability in real-time. A variable rate tool can reduce application rates as high as 50% (Shannon et al., 2018), which is the most critical challenge to address in pecan production. Compared to field crops, there is not much need to be concerned about accuracy and differential correction issues as in a flat two-dimensional field. The challenge for pecan producers is the implementation of variable rate application in a three-dimensional space (i.e., different areas of the tree crown). Specific applications include pesticide application, zinc spray, etc., which require precise coordination of horizontal and vertical movements in real-time (Rosell-Polo et al., 2015) as well as new algorithms and software development.

The second challenge specific to pecan and other tree nuts is that satellite remote-sensing imageries may not work well due to their relatively low resolution. Short-range, ground-based radars and microwaves become more effective sensing solutions in a pecan orchard, especially when a particular application requires a resolution of less than one meter. The limitation of satellite remote-sensing imageries is also due to the three-dimensional nature of pecan orchards management, as previously mentioned. Not everything can be observed from the top of a tree. For instance, drone-based sensing devices may need to fly below or parallel to tree crowns, which requires drone navigation with collision avoidance schemes (Liu et al., 2019). In such an application environment, cameras and LiDAR technologies are often integrated to address shading and light variation issues.
As smart agriculture innovation (e.g., artificial intelligence, IoT, data analytics) propels PA technology applications to the next level, field crops and tree crops also share two common challenges concerning the economics behind PA technologies. First, PA adoption by smart farming operations requires a substantial initial investment in technology and knowledge (or human resources). The cost and complexity of PA have become a major hurdle for small producers to adopt the new technologies (Daberkow and McBride, 2003; Lowenberg-DeBoer and Erickson, 2019). Second, many network-based technologies have an economies-of-scale effect (e.g., pest monitoring). A particular network-based technology needs to be scaled up for all participating farms to benefit from the network effects. The challenge is coordinating the network and scaling up the technology in a community or a region. A related challenge here is engaging small producers in PA technology adoption to harness both the economies of scale and the network effects. As Shannon et al. (2018) pointed out, PA technology adopters tend to cluster around a service provider. Such a spatial clustering pattern can be used to strategically incentivize technology service providers as part of regional economic development policies. The spatial clustering may also be effective for local PA knowledge spillover.

Another emerging challenge for applying PA technologies in both field crops and tree crops is cybersecurity. Security and privacy in smart agriculture have attracted growing attention due to their potentially disastrous consequences, both technologically and financially. As more and more IoT and smart computing technologies for PA rely on internet communication systems, there is increased risk of data theft and cyber-attacks (Gupta et al., 2020). According to a recent US Department of Homeland Security (USDHS) report, the key threats to PA include threats to confidentiality, integrity, and availability (USDHS, 2018). Specific to pecan production, potential malicious attacks will be more likely in the categories of integrity and availability. For instance, a network attack can disrupt a space-based positioning, navigation, and timing (PNT) system that is essential for variable rate applications.

Lastly, there are also region-specific challenges. For example, pecan farms in the Southwest have faced a growing salinity issue associated with irrigation water in recent decades (Walworth, 2011). The situation can become more challenging due to the rising complexity of the new micro-sprinkler system equipped with soil moisture sensors. High salinity not only affects tree health and nut yield, but can also increase system operating and maintenance costs (Lili et al., 2020).

**Future Opportunities**

Existing challenges provide opportunities for future innovation, particularly in terms of developing and implementing PA technologies for pecan production. First, traditional orchard management relies on rules of thumb for activities like fertilization and pesticide applications. Future PA technologies can enable the integration of these activities with other tasks (e.g., yield monitoring, see Figure 3) in a dynamic or even real-time manner. It will push remote-sensing technologies in both spatial and temporal dimensions. For example, machine vision and deep learning can be used to improve short-range sensing technologies unique to tree crop production (Costa et al., 2021). Meanwhile, it will require farms to build or have access to data analytics services to convert sensing data into timely decision making. Sensing is no longer a simple part of crop monitoring. Rather, sensing becomes part of real-time or near-real-time data-driven decision making (DDDM) in orchard
management. Such integration will define the production of pecans and other tree crops for years to come.

**Figure 3. The Integration of Precision and Smart Agriculture Technologies**

![Diagram of precision and smart agriculture technologies]

*Note: Photo by Haoying Wang at Mesilla Valley, New Mexico; edited by Emily Wood and Haoying Wang.*

Second, efficient decision making and management are critical to the success of modern agriculture. In pecan production, many PA technologies are currently at the experimental stage or the lab scale. Eventually, they will face a “scale-up” test, which is both a challenge and an opportunity. At the field scale, some technologies may adapt (e.g., caged drones) while others may integrate themselves into an existing platform or device (e.g., self-driving ATV). It is worth noting that market competition is always an accelerator for innovation and technology adoption. For instance, Mexico has recently become a strong competitor in the pecan business (Hawkes, 2019). Given that the international market is crucial to the US pecan producers, market competition may push the pecan industry to adopt more advanced PA technologies sooner.

Another future opportunity is innovation and entrepreneurship in the technology market. More and more startups emerge in the area of PA (and smart agriculture). It is reasonable to expect that, as the cost of new technologies decreases, more producers will start adopting new PA technologies. Small and medium-sized farms, which play an essential role in rural economic development, may continue facing challenges in technology adoption. In such cases, the availability of customized services through purchasing and rental options can be critical for improving access to technologies (Gallardo et al., 2019). Market (and policy) innovations should play an active role in helping small and medium-sized farms to harness PA technologies.

**Concluding Remarks**
This paper reviews the application of PA technologies in pecan production from both technological and economic perspectives. Although there is an optimistic view of PA technologies’ potential, it is imperative to understand and prepare for the challenges that come with the technology. To transform these challenges and opportunities into economic prosperity, there is a need for entrepreneurship and well-designed policies to address the investment obstacle. Educators should also be ready to innovate agriculture education curriculum to train the workforce to embrace PA opportunities. As PA information technologies expand, it creates an integration of precision
technologies, information systems, and decision-making processes in agricultural production management. It requires agriculture education to adapt to the emerging new demand. On a different aspect, it also requires extension and outreach services to adapt and raise technology awareness among small and medium-sized farms. Technology development and commercialization are important. However, engaging small and medium-sized farms is equally critical for technology diffusion and improvement.

Lastly, it is worth noting that this review only focuses on production-related PA technologies. It does not cover pecan processing technologies that are within the broad PA domain. Nevertheless, the application of processing technologies also has promising prospects. For example, X-ray machine vision inspection systems have been used for identifying pecan defects (Weckler et al., 2015).

References


Adoption Determinants of Precision Agriculture Technologies and Conservation Agriculture: Evidence from South Dakota

By Deepthi E. Kolady1 and Evert Van der Sluis 2

Abstract
Precision agriculture technologies and conservation agriculture practices both have private and public benefits, in the sense that they have the potential to increase producer profitability and reduce environmental externalities. This study investigates the determinants of the adoption of precision technologies and conservation practices, examines whether the two adoption decisions are correlated, and considers impediments to adoption. Results show that the two adoption decisions are positively correlated, and some adoption determinants (farm size, and familiarity with computer use) overlap, while others (land quality and livestock ownership) differ. We also find a positive correlation between the adoption of conservation practices and that of embodied knowledge technologies, but not between the adoption of conservation practices and that of information intensive technologies. Thus, scaling up the joint adoption of precision technologies and conservation practices could be accomplished by designing programs that target large farm operations and those using computers for farm management practices. However, if the policy aim is to broaden the joint adoption of precision technologies and conservation practices among small farm operations, then existing obstacles faced by these operations would need to be addressed.

Introduction
Precision agriculture is defined as a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines them with other information to guide site, plant or animal-specific management decisions to improve resource efficiency, productivity, quality, profitability and sustainability of agricultural production (ISPA 2018). Input use efficiency (i.e., efficiency in the use of seeds, chemicals, fertilizers, fossil fuels, etc.) achieved through precision agriculture technologies (PATs) improves soil health, water quality, and air quality, while maintaining or even improving output/yield (Tey and Brindal 2012, Lambert et al.

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Currently available PATs are broadly classified into two categories: (i) embodied knowledge technologies; and (ii) information intensive technologies. Embodied knowledge technologies do not require any additional skills for the operator to fully utilize them. In other words, the value of the technology is embodied within the machine/equipment. Examples of embodied knowledge technologies include auto-guidance systems and automatic section controls. In contrast, information intensive technologies, such as variable rate system applicators, require specialized skills on the part of the operator to gather and interpret data for the efficient use of inputs/resources (Griffin et al. 2004, Barnes et al. 2019, Kolady et al. 2020).

Conservation agriculture is defined as an application of agricultural practices that improves production while concurrently protecting and enhancing the land resources on which production depends (Pittelkow et al. 2014, Rosa-Schleich et al. 2019). Similar to PATs, conservation agriculture practices (CAPs) enhance soil health and water quality. Examples of CAPs are conservation tillage methods (including no till, reduced till, and strip till) that reduce runoff and soil erosion in comparison to plow-based tillage, and cropping systems that incorporate cover crops (Bewick et al. 2008, Kaspar and Singer 2011). Also, because CAPs may increase soil carbon sequestration and reduce greenhouse gas emissions, they are an important component of carbon market discussions involving agricultural lands (Bowman et al. 2016).

Based on the definitions above, it is clear that both PATs and CAPs can address negative environmental and ecosystem impacts of agricultural production practices and contribute to the long-term economic and environmental sustainability of agricultural production systems.

Because of these private and public benefits, selected federal and state programs and policies support farm-level adoption of PATs and CAPs. Also, due to similarities in their ultimate goals, farmers’ adoption decisions concerning PATs and CAPs are likely correlated. Nevertheless, policies and programs (extension programs, cost share programs, subsidies, etc.) that support the simultaneous adoption of PATs and CAPs are limited. Therefore, gaining an understanding of the factors influencing the adoption of PATs and CAPs and how those adoption decisions are correlated at the farm level is imperative for developing programs and policies that incentivize the simultaneous adoption of these two innovations and that seek to overcome impediments to adoption.

This research investigates the determinants of adoption of PATs and CAPs, examines whether farmers’ adoption decisions regarding the two innovations are correlated, and identifies barriers to adoption. Because many embodied knowledge PATs involve considerable capital expenditures, factors influencing their adoption may differ from those affecting the adoption of information intensive technologies. In order to address this potential issue, we examine the determinants of adopting
embodied knowledge and information intensive technologies – both separately as well as combined. If the adoption determinants are more or less similar and if farmers’ adoption decisions are positively correlated at statistically significant levels, then there is a rationale for developing extension, other education, and financial support programs that enhance the simultaneous adoption of PATs and CAPs. We also identify key impediments to adoption to gain an understanding of farmers’ motivations for not adopting these technologies and practices. The latter is important if the policy aim is to broaden the adoption of precision technologies and conservation practices.

Data and Methods
The data used in this study are based on a survey held among Eastern South Dakota farmers in the spring of 2017, to assess the determinants of the adoption of PATs and CAPs and to learn about their motivations for non-adoption. Intensive production of row crops (corn, soybeans, and wheat) dominates the region, so an accurate identification of the determinants of (not) adopting PATs and CAPs may help in designing effective policies for offsetting some of the negative environmental externalities associated with intensive crop production. We used stratified random sampling to select a representative sample of corn, soybean, and wheat farm operators from the major corn, soybean, and wheat-producing counties in Eastern South Dakota. A total of 1,200 surveys were mailed to the randomly selected producers in three rounds, of which 198 were returned with usable data for most of the questions, resulting in an overall response rate of 18%. The average age of the survey respondents was 59.5 years. As per the 2017 Census, the average age of primary operators in the state was 56.2 years. The average farm size in the study sample was 771 hectares, much higher than the 584 hectares state average in the 2017 Census. While average farm size in the sample exceeds that of the state, farms were equally weighed in the empirical analysis described below.

The survey collected information on production practices, farm characteristics, adoption levels of PATs (including both embodied knowledge and information intensive technologies) and CAPs (such as the use of cover crops, and the implementation of conservation tillage), reasons for adoption and non-adoption of PATs and individual CAPs, and farmer demographics. GPS guidance systems, autosteer, and automatic section controls/shut offs were considered embodied knowledge precision technologies, whereas yield monitors, variable rate systems, prescription field maps, grid soil sampling, crop tissue sampling, and aerial/satellite imagery were categorized as information intensive precision technologies in the study.

No tillage, reduced tillage, and strip tillage were considered forms of conservation tillage.

In order to examine the determinants of adoption and to account for the potential correlation between adoption decisions of PATs and CAPs, a bivariate Probit model was estimated using age, cropland acres, education level (college education or not), land quality (high quality or not), operator off-farm income (yes/no), cattle...
operation (yes/no), and use of computer for farm management purposes (yes/no). We created a dependent variable for embodied knowledge PATs with a value equal to one if a respondent adopted any of the embodied knowledge PATs listed in Table 1, and zero otherwise. Similarly, the variable information intensive PATs has a value of one if a respondent adopted any of the information intensive PATs, and zero otherwise. The variable PATs adoption has a value of one if a respondent adopted any one of the embodied knowledge or information intensive PATs, and zero otherwise. The variable conservation adoption takes the value of one, if a respondent adopted any one of the CAPs listed in Table 1, and zero otherwise.

Results

Table 1 illustrates that there is wide variation among and between the adoption rates of PATs and CAPs. Overall, adoption rates of embodied knowledge PATs exceed those of information intensive precision technologies. The difference in adoption rates of embodied knowledge and information intensive precision technologies indicates that the determinants of the adoption decisions differ at the farm/farmer level for these two types of PATs. Among the information intensive technologies, yield monitors have the highest adoption rate (69%), and aerial/satellite imagery has the lowest adoption rate (31%). As per the USDA data from 2010, 36% of planted corn acres in South Dakota used yield monitor to document yield, compared to the 28% nationally (USDA 2010). Schimmelpfennig (2016) observed that PAT adoption rates in Corn Belt states exceeded the national average. Our study also finds that adoption rate of PATs in our sample from Eastern South Dakota is higher than state and national averages.

Among the conservation tillage types in Table 1, no tillage has the highest adoption rate (50%), followed by reduced tillage (43%), and strip tillage (19%). Compared to conservation tillage, the adoption rate of cover crops is much lower (31%). Wade et al. (2015) documented that CAP adoption rates varied widely by crop and region. As per the 2017 Cropping Systems Inventory from South Dakota, 45% of crop land is in no-till followed by 39% in reduced tillage and mulch tillage and 16% in conventional tillage (NRCS 2017). These numbers are largely similar to the tillage adoption rates among the survey respondents (Table 1).

Adoption summary statistics of the key variables are presented in Table 2. Table 2 shows that adopters of PATs and CAPs tend to have large farms relative to non-adopters and are more familiar with computer applications for farm management.

Results from the bivariate Probit model regression are presented in Table 3 and the marginal effects are presented in Table 4. Column 2 in Table 3 presents the results of the bivariate Probit model using CAPs and embodied knowledge PATs as dependent variables, Column 3 presents the results of the bivariate Probit model using CAPs and information intensive PATs as dependent variables, and Column 4 presents the results of the bivariate Probit model using CAPs and PATs in general (adoption of either embodied knowledge or information intensive PATs) as dependent variables.
Based on results in Table 3, producers with a relatively large farm size who have livestock and who already use computers for farm accounting purposes are more likely to adopt CAPs than their counterparts. However, college-educated producers and those with relatively better land quality are less likely to adopt CAPs than their counterparts.

Similar to CAPs, farm size and familiarity with computer usage in farm accounting increase the likelihood of adoption of PATs. However, differences exist in the marginal effects of these variables on the likelihood of adopting embodied knowledge and information intensive PATs (Table 4). The marginal effect of farm size is higher for the embodied knowledge precision technologies – where technology updates often come with the purchase of new equipment – than for information intensive precision technologies. However, the marginal effect of familiarity with using computers for farm accounting is higher for information intensive PATs than for embodied knowledge PATs. As noted earlier, information intensive technologies generally require additional skills for the operator to gather, analyze, and interpret the data for farm management purposes. Unlike with CAPs, land quality has a positive effect on the likelihood of adopting embodied knowledge PATs, while no such effect is present for information intensive precision technologies.

Unlike with CAPs, results in Tables 3 and 4 show livestock ownership is not a determinant of the adoption of PATs. Older farmers are more likely to adopt embodied knowledge precision technologies than their younger counterparts, while no such effect is present for information intensive precision technologies or for CAPs. In the context of findings by Thompson et al. (2019) – who noted that among some farmers the adoption of selected PATs may be motivated more by convenience than by financial considerations – convenience considerations may play a role among older farmers. Our results also show that operators with off-farm income are less likely to adopt information intensive precision technologies than those who do not have off-farm earnings, while no such effect is present for either embodied knowledge PATs or CAPs.

Overall, the results in Table 3 and 4 show some similarities and differences among and between the determinants of adoption of CAPs and PATs. Our analysis shows that adoption decisions of CAPs and embodied knowledge PATs are correlated at statistically significant levels \((r=0.52, p<0.01)\) while adoption decisions of CAPs and information intensive agriculture practices \((r=0.22)\) are not correlated at statistically significant levels. Our analysis also shows a statistically significant positive correlation between the adoption of CAPs and PATs overall \((r=0.59; p<0.05)\). In efforts to gain a deeper understanding of these findings, it is important to ascertain why farmers refrain from adopting PATs and CAPs. Reasons for non-adoption of PATs and CAPs are presented in Tables 5-7. Because of the high adoption rates of embodied knowledge PATs, the number of non-adopters of any PATs is small among the survey respondents (Table 5). In the case of PATs, two-thirds \((66.7\%)\) of the non-adopters viewed the high cost of equipment as an (either very or moderately)
important reason for not adopting PATs. This was followed by a perceived uncertainty of making a profit using the technology, the technology’s complexity, and satisfaction with current technology, each identified by 60% of the respondents as important reasons for not adopting PATs. The remaining reasons for not adopting PATs were listed by fewer than 50% of the non-adopters, and include the perceived lack of profitability, the risks involved with making the investment, uncertain environmental benefits, lack of information, and lack of attractiveness of federal programs (Table 5).

Regarding obstacles to adopting conservation tillage methods, 84.6% of the respondents who did not incorporate conservation tillage methods in their farming operations indicated that the perceived lack of profitability was an important (either very or moderately important) reason for not adopting conservation tillage. Other reasons identified by these farmers as important impediments to adopting conservation tillage were that they were satisfied with current practices (as indicated by 78.6% of the respondents), high equipment costs (67.9%), and time constraints (59.2%). Further, uncertainty about the environmental benefits and lack of information were cited by fewer than one-half of this those who had not adopted conservation practices (Table 6).

As pointed out in Table 1, fewer than one out of three respondents indicated using cover crops. Table 7 shows that just over three out of four (76.8%) of these non-adopters of cover crops identified time conflicts between cover crop planting and cash crop harvesting activities as (very or moderately) important determinants of not adopting cover crops, followed by satisfaction with current practices, as indicated by 69.5% of these farmers as an important determinant of non-adoption. Among the remaining factors – uncertainty about yield benefits, lack of profitability, uncertainty about the environmental benefits, the risk of investing in cover crops, and a lack of attractiveness to farm programs – each was perceived as an important determinant of not adopting cover crops by fewer than one-half of the respondents who had not adopted cover crops in their farming practices.

Conclusions
Findings from our study show that adoption decisions regarding CAPs and PATs are positively correlated at statistically significant levels and some of the determinants, such as farm size, and computer usage familiarity, have similar effects on both adoption decisions. When disaggregating PATs, the positive correlation continues to hold between CAPs and embodied knowledge PATs, but not between CAPs and information intensive PATs. However, factors such as land quality and livestock ownership have differing effects on the adoption of CAPs and PATs. The positive correlation between CAPs and PATs overall and between CAPs and embodied knowledge PATs specifically suggest that programs targeting conservation – such as the Conservation Stewardship Program – may not only advance CAP adoption but may have spillover effects with regards to PAT adoption. Vice versa, when policymakers consider developing programs that target the adoption of PATs overall,
and particularly embodied knowledge PATs, program implementation may have positive spillovers for CAP adoption.

For both PATs and CAPs, a common obstacle for non-adopters is their satisfaction with current practices. Also, for both PATs and conservation tillage, important barriers to adoption are the perceived high costs of equipment, as well as concerns regarding profitability. Separately, for PATs, the technology’s perceived complexity was a key reason identified by non-adopters for not investing in the technology, whereas facing time constraints was noted by non-adopters as a key reason for not adopting conservation tillage practices. In the case of PATs, key obstacles to adoption for non-adopters were the perceived costs, complexity, and profit uncertainty associated with the technology, as well as satisfaction with current practices.

On the one hand, these findings imply that extension and other education programs, as well as financial support programs targeted to large farm operations and those already using computers for farm management practices may be effective approaches to scaling up the simultaneous adoption of CAPs and PATs, by targeting producers based on their demographics and farm characteristics. On the other hand, if public policies seek to encourage a more equitable and broad-based participation in sustainable agricultural practices, it may be possible to overcome real and perceived obstacles which keep farm operators from adopting CAPs and PATs.

References


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. Staff paper #04-06, Department of Agricultural Economics, Purdue University.


<table>
<thead>
<tr>
<th>Type of PATs</th>
<th>Adoption rate (%)</th>
<th>Type of conservation practices</th>
<th>Adoption rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Embodied knowledge</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPS guidance system</td>
<td>75.8</td>
<td>No tillage</td>
<td>50</td>
</tr>
<tr>
<td>Autosteer</td>
<td>73.7</td>
<td>Reduced tillage</td>
<td>43.4</td>
</tr>
<tr>
<td>Automatic section control/shut offs</td>
<td>55.1</td>
<td>Strip tillage</td>
<td>19.2</td>
</tr>
<tr>
<td><strong>Information intensive</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield monitor</td>
<td>68.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variable rate system</td>
<td>50.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prescription field maps</td>
<td>50.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grid soil sampling</td>
<td>44.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop tissue sampling</td>
<td>37.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerial/satellite imagery</td>
<td>30.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cover crops</strong></td>
<td></td>
<td></td>
<td>31.3</td>
</tr>
</tbody>
</table>
### Table 2: Summary Statistics of Key Variables Used in Bivariate Probit Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Embodied knowledge PATs</th>
<th>Information intensive PATs</th>
<th>PATs</th>
<th>CAPs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Adoption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(58.7)</td>
<td>(58.6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.5)</td>
<td>(12.0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cropland (acres)</strong></td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(506.9***</td>
<td>(2200.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(332.3)</td>
<td>(2504.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>College Education (0/1)</strong></td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Land quality (0/1)</strong></td>
<td>0.4</td>
<td>0.3</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Operator off farm income (0/1)</strong></td>
<td>0.4</td>
<td>0.2</td>
<td>0.4**</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Livestock (0/1)</strong></td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Computer use for farm accounting (0/1)</strong></td>
<td>0.4**</td>
<td>0.7</td>
<td>0.3***</td>
<td>0.7</td>
</tr>
</tbody>
</table>

**Note:** ***, **, and * indicate mean values are statistically significantly different at the 1%, 5%, and 10% levels, respectively, between adopters and non-adopters of each technology/practice.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Conservation agriculture practices</th>
<th>Conservation agriculture practices</th>
<th>Conservation agriculture practices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>0.018 (0.011)</td>
<td>0.016 (0.011)</td>
<td>0.017 (0.011)</td>
</tr>
<tr>
<td>Cropland (0,000 acres)</td>
<td>0.255* (0.134)</td>
<td>0.270** (0.138)</td>
<td>0.264* (0.136)</td>
</tr>
<tr>
<td>College education (0/1)</td>
<td>-0.700** (0.286)</td>
<td>-0.744** (0.291)</td>
<td>-0.736** (0.289)</td>
</tr>
<tr>
<td>Land quality (0/1)</td>
<td>-1.127*** (0.287)</td>
<td>-1.118*** (0.290)</td>
<td>-1.108*** (0.285)</td>
</tr>
<tr>
<td>Operator off farm income (0/1)</td>
<td>0.174 (0.339)</td>
<td>0.239 (0.346)</td>
<td>0.167 (0.327)</td>
</tr>
<tr>
<td>Livestock (0/1)</td>
<td>0.477 (0.294)</td>
<td>0.531* (0.292)</td>
<td>0.480* (0.285)</td>
</tr>
<tr>
<td>Technology use (0/1)</td>
<td>0.981*** (0.316)</td>
<td>0.990*** (0.311)</td>
<td>0.995*** (0.310)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.400 (0.820)</td>
<td>-0.336 (0.813)</td>
<td>-0.340 (0.794)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Embodied knowledge PATs</th>
<th>Information intensive PATs</th>
<th>PATs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>0.022* (0.013)</td>
<td>0.009 (0.014)</td>
<td>0.020* (0.012)</td>
</tr>
<tr>
<td>Cropland (1,000 acres)</td>
<td>1.533*** (0.325)</td>
<td>0.778*** (0.292)</td>
<td>1.642*** (0.431)</td>
</tr>
<tr>
<td>College Education (0/1)</td>
<td>-0.070 (0.304)</td>
<td>-0.329 (0.307)</td>
<td>-0.504 (0.386)</td>
</tr>
<tr>
<td>Land quality (0/1)</td>
<td>0.559* (0.316)</td>
<td>0.475 (0.353)</td>
<td>0.718* (0.386)</td>
</tr>
<tr>
<td>Operator off farm income (0/1)</td>
<td>-0.004 (0.334)</td>
<td>-0.707** (0.330)</td>
<td>-0.248 (0.395)</td>
</tr>
<tr>
<td>Livestock (0/1)</td>
<td>0.261 (0.302)</td>
<td>-0.178 (0.314)</td>
<td>0.065 (0.377)</td>
</tr>
<tr>
<td>Technology use (0/1)</td>
<td>0.566* (0.309)</td>
<td>1.139*** (0.307)</td>
<td>0.933** (0.384)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.211** (0.990)</td>
<td>-0.624 (1.040)</td>
<td>-1.473 (1.075)</td>
</tr>
<tr>
<td>Rho</td>
<td>0.517*** (0.517)</td>
<td>0.222 (0.222)</td>
<td>0.586** (0.586)</td>
</tr>
<tr>
<td>Wald Chi 2</td>
<td>78.85</td>
<td>72.31</td>
<td>64.85</td>
</tr>
</tbody>
</table>

| N                                        | 163                     | 162                       | 163                          |

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
### Table 4: Marginal Effects of Variables from the Bivariate Probit Model Regression

<table>
<thead>
<tr>
<th>Variable</th>
<th>Conservation agriculture practices</th>
<th>Conservation agriculture practices</th>
<th>Conservation agriculture practices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Cropland (acres)</td>
<td>0.045*</td>
<td>0.047*</td>
<td>0.046*</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.024)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>College Education (0/1)</td>
<td>-0.122**</td>
<td>-0.129***</td>
<td>-0.129***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Land quality (0/1)</td>
<td>-0.197***</td>
<td>-0.194***</td>
<td>-0.195***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.046)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Operator off farm income (0/1)</td>
<td>0.030</td>
<td>0.041</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.060)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>Livestock (0/1)</td>
<td>0.083*</td>
<td>0.093*</td>
<td>0.084*</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.050)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Technology use (0/1)</td>
<td>0.171***</td>
<td>0.172***</td>
<td>0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.053)</td>
<td>(0.053)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Embodied knowledge PAT</th>
<th>Information intensive PATs</th>
<th>PATs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>0.004*</td>
<td>0.001</td>
<td>0.002*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Cropland (acres)</td>
<td>0.242***</td>
<td>0.123***</td>
<td>0.169***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.043)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>College Education (0/1)</td>
<td>-0.011</td>
<td>-0.052</td>
<td>-0.052</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.047)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Land quality (0/1)</td>
<td>0.088*</td>
<td>0.075</td>
<td>0.074*</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.054)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Operator off farm income (0/1)</td>
<td>-0.001</td>
<td>-0.112**</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.050)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Livestock (0/1)</td>
<td>0.041</td>
<td>-0.028</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.050)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Technology use (0/1)</td>
<td>0.090*</td>
<td>0.180***</td>
<td>0.097**</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.047)</td>
<td>(0.040)</td>
</tr>
</tbody>
</table>

***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
<table>
<thead>
<tr>
<th>Reason</th>
<th>N</th>
<th>Not Important</th>
<th>Slightly Important</th>
<th>Moderately Important</th>
<th>Very Important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not profitable</td>
<td>11</td>
<td>4 (36.4)</td>
<td>2 (18.2)</td>
<td>2 (18.2)</td>
<td>3 (27.3)</td>
</tr>
<tr>
<td>Uncertain profits</td>
<td>10</td>
<td>3 (30.0)</td>
<td>1 (10.0)</td>
<td>4 (40.0)</td>
<td>2 (20.0)</td>
</tr>
<tr>
<td>Complex technology</td>
<td>10</td>
<td>3 (30.0)</td>
<td>1 (10.0)</td>
<td>2 (20.0)</td>
<td>4 (40.0)</td>
</tr>
<tr>
<td>High costs of equipment</td>
<td>12</td>
<td>3 (25.0)</td>
<td>1 (8.3)</td>
<td>2 (16.7)</td>
<td>6 (50.0)</td>
</tr>
<tr>
<td>Risky investment</td>
<td>10</td>
<td>5 (50.0)</td>
<td>1 (10.0)</td>
<td>2 (20.0)</td>
<td>2 (20.0)</td>
</tr>
<tr>
<td>Uncertain about environmental benefits</td>
<td>10</td>
<td>5 (50.0)</td>
<td>1 (10.0)</td>
<td>3 (30.0)</td>
<td>1 (10.0)</td>
</tr>
<tr>
<td>Lack of information</td>
<td>10</td>
<td>4 (40.0)</td>
<td>3 (30.0)</td>
<td>2 (20.0)</td>
<td>1 (10.0)</td>
</tr>
<tr>
<td>Federal programs are unattractive</td>
<td>10</td>
<td>4 (40.0)</td>
<td>3 (30.0)</td>
<td>2 (20.0)</td>
<td>1 (10.0)</td>
</tr>
<tr>
<td>Satisfied with the current practice</td>
<td>10</td>
<td>3 (30.0)</td>
<td>1 (10.0)</td>
<td>2 (20.0)</td>
<td>4 (40.0)</td>
</tr>
</tbody>
</table>

Note: N is the number of responses received. Columns 3-6 show the frequency and percentage of the responses in parentheses.
Table 6: Reasons for Non-adoption of Conservation Tillage by Non-adopting Survey Respondents*

<table>
<thead>
<tr>
<th>Reason</th>
<th>N</th>
<th>Not Important</th>
<th>Slightly Important</th>
<th>Moderately Important</th>
<th>Very Important</th>
</tr>
</thead>
<tbody>
<tr>
<td>High cost of equipment</td>
<td>28</td>
<td>6 (21.4)</td>
<td>3 (10.7)</td>
<td>7 (25.0)</td>
<td>12 (42.9)</td>
</tr>
<tr>
<td>Uncertain about environmental benefits</td>
<td>25</td>
<td>5 (20.0)</td>
<td>8 (32.0)</td>
<td>7 (28.0)</td>
<td>5 (20.0)</td>
</tr>
<tr>
<td>Not profitable</td>
<td>26</td>
<td>2 (7.7)</td>
<td>2 (7.7)</td>
<td>9 (34.6)</td>
<td>13 (50.0)</td>
</tr>
<tr>
<td>Time constraints</td>
<td>27</td>
<td>7 (25.9)</td>
<td>4 (14.8)</td>
<td>8 (29.6)</td>
<td>8 (29.6)</td>
</tr>
<tr>
<td>Lack of information</td>
<td>26</td>
<td>9 (34.6)</td>
<td>9 (34.6)</td>
<td>4 (15.4)</td>
<td>4 (15.4)</td>
</tr>
<tr>
<td>Satisfied with the current practices</td>
<td>28</td>
<td>2 (7.1)</td>
<td>4 (14.3)</td>
<td>7 (25.0)</td>
<td>15 (53.6)</td>
</tr>
<tr>
<td>Federal programs are unattractive</td>
<td>27</td>
<td>13 (48.2)</td>
<td>7 (25.9)</td>
<td>3 (11.1)</td>
<td>4 (14.8)</td>
</tr>
</tbody>
</table>

Note: N is the number of responses received. Columns 3-6 show the frequency and percentage of the responses in parentheses.
<table>
<thead>
<tr>
<th>Reason</th>
<th>N</th>
<th>Not Important</th>
<th>Slightly Important</th>
<th>Moderately Important</th>
<th>Very Important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not profitable</td>
<td>108</td>
<td>26 (24.8)</td>
<td>32 (30.5)</td>
<td>32 (30.5)</td>
<td>15 (14.3)</td>
</tr>
<tr>
<td>Planting time conflicts with harvest of cash crop</td>
<td>112</td>
<td>15 (13.4)</td>
<td>11 (9.8)</td>
<td>37 (33.0)</td>
<td>49 (43.8)</td>
</tr>
<tr>
<td>Uncertain about the environmental benefits</td>
<td>106</td>
<td>32 (30.2)</td>
<td>32 (30.2)</td>
<td>32 (30.2)</td>
<td>15 (13.4)</td>
</tr>
<tr>
<td>Uncertain about yield benefits</td>
<td>106</td>
<td>27 (25.5)</td>
<td>28 (26.4)</td>
<td>33 (31.1)</td>
<td>18 (17.0)</td>
</tr>
<tr>
<td>Risky investment</td>
<td>106</td>
<td>33 (31.1)</td>
<td>34 (32.1)</td>
<td>27 (25.5)</td>
<td>12 (11.3)</td>
</tr>
<tr>
<td>Federal programs are unattractive</td>
<td>106</td>
<td>44 (41.5)</td>
<td>20 (18.9)</td>
<td>29 (27.4)</td>
<td>13 (12.3)</td>
</tr>
<tr>
<td>Satisfied with the current practices</td>
<td>115</td>
<td>16 (13.9)</td>
<td>19 (16.5)</td>
<td>45 (39.1)</td>
<td>35 (30.4)</td>
</tr>
</tbody>
</table>

Note: N is the number of responses received. Columns 3-6 show the frequency and percentage of the responses in parentheses.
Recent Trends in PA Technology Adoption and Bundling in Corn Production: Implications for Farm Consolidation

By Nathan DeLay¹ and Haden Comstock²

Acknowledgements: We thank the anonymous reviewer for their helpful comments. This research was supported by funding from the Purdue Center for Commercial Agriculture and the National Institute of Food and Agriculture, U.S. Department of Agriculture, Hatch project 1019254. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture.

Abstract
We analyze recent trends in precision agriculture (PA) technology adoption by U.S. corn growers using nationally-representative data from the Agricultural and Resource Management Survey (ARMS). We show that corn production is increasingly reliant on PA tools and practices, but that adoption skews toward larger operations. Large-scale operations are also responsible for a greater share of the growth in PA in recent years. Adoption patterns are consistent with sequential adoption and path dependency in PA. These results imply significant economies of scale in PA, which may accelerate existing trends in farm consolidation.

Keywords: precision agriculture, technology adoption

Introduction
Precision agriculture (PA) technologies allow producers to manage crops more accurately by exploiting within-field variability in soils and topography. By optimizing input applications, PA promises to reduce operating costs without sacrificing output. Adoption of PA has risen steadily among Corn Belt farms since the commercialization of the yield monitor in the early 1990s. While individual PA technologies address specific management decisions, the impact of PA adoption is likely cumulative, meaning the benefits are realized when complementary tools are integrated to form an overall precision farming strategy. Despite significant growth in the breadth and depth of precision farming tools, take up has somewhat lagged expectations. Economies of scale in PA may be a contributing factor, as adoption rates are shown to vary significantly by farm size (Schimmelpfennig, 2016).

The primary motivation behind farmers’ adoption of PA technology and data collection is to reduce costs, improve management decisions, and increase profitability. Schimmelpfennig (2016) finds small but positive effects of PA on farm operating profits, but effects vary by technology type. Profitable implementation of PA also depends on the quality of information and data that informs its

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use (Bullock et al., 2009; Tenkorang and Lowenberg-DeBoer, 2008; Bullock and Lowenberg-DeBoer, 2007; Bullock et al., 2002; Bullock and Bullock, 2000). Beyond profitability, some PA technologies are perceived to increase the convenience of farming by automating certain tasks (Thompson et al., 2019).

Bundling is an important aspect in PA adoption. Tools such as grid soil sampling and variable rate technology (VRT) can be combined to form complementary technology packages, which can either work directly together or be used individually (Schimmelpfennig and Lowenberg-DeBoer, 2020). While PA may be most impactful when technologies are used in concert, new technologies are often adopted in sequential order. Farms first adopt elemental bundles, and then layer in more advanced technologies as time goes on (Khanna, 2001; Khanna et al., 1999; Leathers and Smale, 1991).

While a number of farm and operator characteristics influence new technology adoption patterns (e.g., uncertainty, risk preferences, credit constraints), farm size is often cited as a potential barrier to PA adoption (Schimmelpfennig, 2016; Khanna et al., 1999). PA technologies—particularly equipment like variable rate applicators—involve large up-front investments. This will naturally deter small operations who cannot spread the fixed costs over a large number of acres or output. The effects of PA on farm profitability appear small but may become meaningful when aggregated over a large scale. This aggregation effect will be even greater in the presence of high fixed costs. Large farms are also more likely to have the degree of variability in soils and topography to warrant the use of site-specific crop management. Lastly, successful implementation of PA requires knowledge of the spatial differences in yield response within the field (Bullock et al., 2009). The capacity for this kind of on-farm research may again privilege large farms.

In this paper, we investigate how the adoption of PA has changed over time using the most recent available data from the Agricultural Resource Management Survey (ARMS) of corn producers. By comparing the adoption trends for specific technologies and technology bundles by farm and by acreage, we can better understand the importance of scale economies within PA. Results have implications for consolidation within U.S. corn production.

Data and Methods
The United States Department of Agriculture (USDA) Economic Research Service (ERS) and National Agricultural Statistical Service (NASS) administer the Agricultural Resource Management Survey (ARMS) yearly for a select commodity. ARMS documents farm- and field-level management practices, input application, farm and operator characteristics, and technology adoption (including PA) for a nationally-representative sample of producers. We use data from the last three available ARMS for corn operations: 2005, 2010, and 2016. The 2005 and 2010 questionnaires contain the same set of PA adoption variables while the 2016 survey was altered and expanded to cover usage of farm data and digital tools. Farm respondents are expanded using sampling weights assigned by NASS to construct PA adoption estimates for all corn producers in the U.S. We also look at adoption rates for PA in terms of the number of acres on which various technologies and technology bundles were used to raise corn.

Due to the nationally-representative nature of the ARMS survey, our study applies to the entire U.S. However, it should be noted that because the Corn Belt states contain a high concentration of corn operations, this area will be highly representative in our results. Nearly half of
the analyzed sample is located in the “Heartland” region (the area generally encompassing the Corn Belt as defined by the USDA ERS Farm Resource Regions).

**Precision Agriculture Adoption Trends**
Table 1 summarizes trends in adoption rates for individual PA technologies across U.S. corn farms for 2005, 2010, and 2016. Figures 1 and 2 depict trends in adoption rates for key technologies. Below we examine these trends by technology type.

**Yield Monitoring and Yield Mapping**
Yield monitors remain the most commonly used type of PA technology both in terms of farms and acres. As of 2016, over half of all corn farms had a yield monitor and were used on nearly 70% of all corn acres. However, adoption grew more rapidly between 2005 and 2010 than between 2010 and 2016, particularly in terms of planted acreage. Farm-level adoption of yield monitors rose by 15 percentage points from 2005 to 2010 and by 10 percentage points between 2010 and 2016. By contrast, the proportion of planted corn acres using a yield monitor rose by 20 percentage points from 2005 to 2010 and only seven percentage points from 2010 to 2016.

Yield monitoring technology has been commercially available since 1992 and is widely considered an “entry-level” PA technology which integrates with more advanced packages. Yield monitoring technology often comes standard with new combine harvesters, meaning part of these adoption trends are likely explained by capital replacement and the factors that influence it. The relatively high changes in yield monitoring among corn farmers vs. corn acreage implies that, at least for the time period examined here, yield monitoring became more popular among smaller, late adopting corn farms.

Yield monitoring technology can estimate moisture content at harvest, allowing farmers to determine whether their grain meets elevator standards or if drying is necessary. Forty-three percent of farms used a yield monitor to inform grain drying decisions in 2016, or 82% of yield monitor users, by far the most common usage of yield monitor data. Trends in the use of yield monitors for grain drying decisions reflect the growth in on- and off-farm grain storage capacity since the early 2000s.

Managers can also use yield monitor information to identify areas within a field that are prone to excess moisture accumulation. Almost one fifth of yield monitor adopters used the technology to...
inform tile drainage additions or improvements in 2016, a 40% increase from 2005. Large operations are significantly more likely to use yield monitor data for this purpose.

Finally, producers can leverage yield monitor information to renegotiate cropland lease agreements. Data on historic yields, soil moisture retention, and grain moisture content all enhance the information available for the operator to calculate the true value of rented farmland. Yet less than 10% of operations with yield monitor technology reported using this information in farm lease negotiations in 2016. Given that less than half of corn operations rented fields in 2016, the share in Table 1 is misleading. Among yield monitor adopters and cropland renters, use of yield monitor information to renegotiate leases grew ten-fold, from less than 4% in 2005 to over 14% in 2016. With a per-acre adoption rate twice the size of the per-farm adoption rate, using yield monitor data in lease negotiations is the most heavily skewed toward large operations. The acceleration in this practice implies a growing awareness of precision agriculture applications for farmland rental markets, at least among commercial operators who are the most likely to lease farmland. In the future, sharing yield maps, satellite imagery, and other PA data could become a normal part of farmland lease arrangements (Coble et al, 2018; Griffin et al., 2016).

Yield mapping is the most common yardstick for measuring successful implementation of yield monitor technology. However, these results indicate that operators are more likely to use yield monitor data to inform storage, marketing, and investment decisions—discrete changes that can have large impacts on profitability—than fine-scale input decisions, where the effects of those decisions are less discernable. As grain storage, tile drainage, and farm data sharing become more common across the Corn Belt, yield monitor data will grow in importance.

Guidance Systems
GPS guidance system adoption has risen from 7% of corn farms (15% of planted acres) in 2005 to 40% of farms (61% of acres) in 2016. While GPS guidance adoption remains skewed toward large operations, guidance technology saw the largest decline in the ratio of acre-level adoption to farm-level adoption. In 2005, the percentage of corn acres using guidance was twice that of corn operations. By 2016, this ratio had fallen to 1.5, suggesting the technology is increasingly within reach for smaller operations. Guidance systems confer multiple benefits to producers that may be scale neutral—creating value for small farms. One is the ability to harvest and apply inputs more efficiently by reducing overlap, potentially cutting costs on a per-acre basis. Another is convenience—a feature that may not directly affect profitability but that nonetheless increases producer utility (Thompson et al., 2019).

Soil Mapping
The practice of creating GPS soil maps grew modestly from 2005 to 2010 but was flat between 2010 and 2016. Unlike other PA practices, soil mapping acts as an intermediate input for precision applications. It is often coupled with other PA practices, mainly yield monitoring, yield mapping, and variable rate technology (VRT) to relate yield outcomes to soil properties and inform seed or

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3 The soil mapping question was revised in the 2016 survey making the question more specific. The flat change in adoption between 2010 and 2016 may be partly as a result of this change.
chemical applications. Performing GPS soil mapping in isolation has not been linked to cost savings (Schimmelpfennig, 2016).

**Variable Rate Technology**

Overall, use of VRT in corn production remains modest at 25% of corn farms and 38% of corn acreage, though adoption rates and trends differ considerably across application types. Of the three types of VRT, variable rate (VR) seeding has experienced the most rapid growth in adoption. Close to 60% of farmers who reported using any VRT used the technology for seeding purposes in 2016, up from 23% in 2005. As shown in Figures 1 and 2, most of the rise in popularity of VR for seeding corn took place between 2010 and 2016, when adoption rates tripled. Relative to VR fertilization, VR seeding is a more recent phenomenon, which may explain its high growth relative to other forms of VRT in recent years. Planters bought between 2010 and 2016 were more likely to come with VR seeding capability and digital tools that generate plant population recommendations.

VR fertilizer application remains the most common form of VRT, though it is growing less rapidly. As of 2016, 19% of all corn producers (29% of corn acres) used VRT for nutrient application. Though the effects of VR nutrient management on profitability are mixed, the practice has been shown to reduce variable costs and enhance nitrogen productivity when combined with detailed soil information (Schimmelpfennig and Ebel, 2016; Khanna, 2001). The lack of consensus on VR fertilizer’s impact may be a limiting factor in its growth.

VR pesticide applications is both the newest and least common form of VRT at less than 10% of corn farms and acres in 2016. Interestingly, VRT for pesticides has the lowest ratio of acre-level adoption to farm-level adoption. Novel technologies are typically adopted first by large operations, which would cause the percent of acres using VRT pesticides to be significantly higher than the percent of farms.

**Drone, Satellite, and Aerial Imagery**

As of 2016, drone or aerial (including satellite) imagery is the least adopted practice among the examined PA technologies, both in terms of corn farms (4%) and planted acreage (7%). Imagery is also the only technology to show a decline from 2010 to 2016 despite significant advancements in drone and satellite technology during this time period. Note that the 2016 ARMS changed the questions related to drone and aerial imagery to measure use of these tools more directly for data collection and mapping. Raising the standard of what is considered use of the technology may partially explain the drop in adoption. Nevertheless, the 2016 survey does not indicate widespread active use of these technologies. However, since the 2016 survey, satellite imagery resolution has improved, and costs have fallen.

**Trends in Precision Agriculture Technology Bundles**

PA implementation may be best measured by the extent to which farms layer multiple complementary technologies to create a systems approach to site-specific management. 4 Bundling of

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4 Note that the 2016 ARMS broadened the PA questions to include new technologies (e.g., crop and soil sensors and data analysis tool). For comparability, we calculate the number of PA technologies adopted based on a common set of technologies that are typically analyzed in the literature: yield monitors, yield mapping, guidance systems, soil mapping, VRT, and aerial imagery.
PA technologies can lead to positive outcomes, but benefits vary by adoption pattern and performance metric (Schimmelpfennig and Ebel, 2016; Khanna, 2001). Studies show that the timing and intensity of technology bundle adoption varies with farm size (Khanna et al., 1999; Feder and Umali, 1993). According to ARMS, the mean number of PA technologies adopted by corn farms has increased from 0.68 in 2005, to 1.67 in 2016, though most of this increase occurred prior to 2010. Figure 3 shows the trends in average technologies adopted by farm size category. Even by 2016, farms with under 250 acres of corn adopted less than one PA technology type, indicating a low capacity for technology bundling among small operations. Interestingly, it is the mid-sized farms (those between 500 and 2,000 acres of planted corn), not the largest farms (those with 2,000 acres or more) that exhibit the most dramatic increase in the number of technologies adopted between 2005 and 2016. Large farms actually show no change in their intensity of adoption from 2010 to 2016—at least for the standard PA technologies included here (see footnote 2). Another notable feature is the mean number of technologies appears to be bounded from above at three technologies, suggesting that there is limited capacity for multiple technologies, even among the largest operations.

To explore this more deeply, we select seven commonly used PA bundles and analyze their adoption trends over time. Table 2 reports the share of corn farms adopting each package and the share of corn acreage using each package by year. For comparison, we include the exclusive adoption of a yield monitor as the “base-level” package. The adoption of “higher order” PA bundles grew in every case from 2005 to 2016, though there are some differences in the pattern and intensity of growth across bundles. Figures 4 and 5 illustrate these trends by corn farms and corn acres, respectively. In 2005, the most commonly adopted bundle by corn farms was a yield monitor only with just over 12% of farms, while in 2010 and 2016, the most common packages were yield monitors with yield mapping (YM + Ymap) and yield monitoring with GPS guidance (YM + GPS).

GPS guidance enabled bundles experienced the most rapid growth over the 2005-2016 period. This makes sense given that GPS guidance enhances, and in some cases is required by, other PA technologies (e.g., mapping technologies and variable rate applicators). Notably, three and four technology packages have become more common in recent years. For example, using yield monitors, yield mapping, and GPS guidance (YM + Ymap + GPS) grew from 3% of corn farms and 5% of corn acreage to become the third most common PA bundle at over one-fourth of farms and 41% of planted acres.

To measure the importance of scale in PA bundling, we look at changes in acre-level adoption rates relative to changes in farm-level adoption rates between 2005 and 2016. Differences in adoption rates and ratios of relative changes are displayed in Figure 6. A ratio above one indicates that larger farms (those responsible for a larger share of U.S. corn production) were more likely to adopt the technology bundle during the 2005-2016 period. A clear pattern emerges from Figure 6; bundles with more technologies grew more as a percentage of corn acres than they did as a percentage of corn operations. Bundles of three or more PA technologies grew about 60% faster on an acreage basis than they did on a farm basis. The bundle of YM + VRT was the only two-technology bundle with a ratio that high. Adoption of the most basic PA bundle YM + Ymap had the most balanced adoption path, with a ratio of 1.33.

Conclusion
We analyze recent trends in precision agriculture technology adoption by U.S. corn producers using data from the USDA Agricultural and Resource Management Survey (ARMS). Consistent with previous findings, we find overall usage of PA expanded between 2005 and 2016, but trends in adoption differed by time period. Though most PA technologies grew in popularity, the pace of adoption appears to have slowed somewhat in recent years. This may indicate a degree of saturation for the standard PA technologies (yield monitoring, yield mapping, soil mapping, guidance systems, variable rate technology (VRT), and aerial imagery).

Trends also varied by technology type and technology bundle. GPS guidance and guidance-enabled technology packages have seen rapid take up by corn growers, while novel tools such as unmanned aerial vehicles (UAVs) and satellite imagery have lagged. In all cases, the proportion of acres using a given technology or technology package exceeds the proportion of farm operations using the technology. Additionally, the rate of growth in acre-level adoption greatly exceeds the rate of growth in farm-level adoption for most technology packages. This pattern is especially true for bundles of three or more technologies (e.g., using a yield monitor, GPS guidance, and VRT). Relative adoption trends show that large farms are consistently more likely to adopt PA technologies, particularly technology packages consisting of multiple tools and practices.

Adoption patterns found here are generally consistent with the sequential adoption models in PA, where farms first adopt a “base level” technology, then stack more advanced technologies in piece-wise fashion (Khanna et al., 1999). This path dependence means that as more farms adopt upstream PA bundles (e.g., yield monitoring and GPS yield mapping), VRT and other advanced practices will become more common. Results of this analysis suggest two things. One, use of PA in U.S. corn production will likely continue, but the overall pace may slow for certain technology types as they face saturation by innovators and early adopters (Rogers, 1962). Two, growth—particularly for advanced PA bundles—will be skewed toward large operations that are better equipped to offset the fixed investment costs and aggregate the incremental benefits of managing crops on a granular scale. If these small benefits add up to meaningful production advantages at scale, PA could be a driver of future farm consolidation (Macdonald et al., 2018). Though not addressed in this paper, there are meaningful differences in PA adoption across corn producing regions. Corn Belt farms are significantly more likely to adopt most PA technologies than corn farms in other regions. They also contribute close to half of all U.S. corn acreage. To the extent to which PA contributes to farm consolidation, the effects will be most concentrated in the Midwestern corn producing states.

The findings of this paper can inform various policy discussions. Public-private investment in rural broadband could increase usage of precision farming technologies, which may favor large farms disproportionately. Alternatively, small farms could become more competitive by adopting certain PA technologies (e.g., by enhancing their efficiency or lowering their input costs) but are unlikely to do so due to the high investment costs and uncertain benefits. Policymakers looking to incentivize technology adoption should consider these possibilities.

References


Figure 1. Precision Agriculture Adoption Trends by Corn Farms, 2005-2016

Figure 2. Precision Agriculture Adoption Trends by Planted Corn Acreage, 2005-2016
Figure 3: Mean Number of PA Technologies Adopted by Farm Size, 2005-2016

Figure 4: Adoption of PA Bundles by Corn Farms, 2005-2016
Figure 5: Adoption of PA Bundles by Corn Acreage, 2005-2016

Figure 6: Changes in Adoption Rates of PA Bundles, 2005-2016
Table 1. Precision Agriculture Technology Adoption (2005-2016)

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>2005 (n=2,145)</th>
<th>2010 (n=2,633)</th>
<th>2016 (n=1,819)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% of corn farms 2005</td>
<td>% of corn acres 2005</td>
<td>% of corn farms 2010</td>
</tr>
<tr>
<td>Yield monitor</td>
<td>0.27</td>
<td>0.42</td>
<td>0.43</td>
</tr>
<tr>
<td>GPS yield map</td>
<td>0.12</td>
<td>0.19</td>
<td>0.21</td>
</tr>
<tr>
<td>Yield monitor - grain drying</td>
<td>0.24</td>
<td>0.36</td>
<td>0.35</td>
</tr>
<tr>
<td>Yield monitor - tile drainage</td>
<td>0.05</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>Yield monitor - negotiate</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>GPS soil map&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.09</td>
<td>0.15</td>
<td>0.14</td>
</tr>
<tr>
<td>VRT any</td>
<td>0.09</td>
<td>0.12</td>
<td>0.17</td>
</tr>
<tr>
<td>VR seeding&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>VR fertilizer</td>
<td>0.08</td>
<td>0.10</td>
<td>0.15</td>
</tr>
<tr>
<td>VR pesticides</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>GPS guidance&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.07</td>
<td>0.15</td>
<td>0.26</td>
</tr>
<tr>
<td>Drone/aerial imagery&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.03</td>
<td>0.06</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Notes: Source: USDA ARMS Phase II for corn 2005, 2010, 2016. Summary statistics represent all corn fields in their respective years using expansion weights provided by USDA NASS. <sup>a</sup> Question changed between 2010 and 2016 surveys. <sup>b</sup> Planters bought between 2010 and 2016 were more likely to come w/ VR seeding capability. <sup>c</sup> GPS guidance systems include both autosteer and light bar technology.
Table 2. Precision Agriculture Technology Adoption Bundles (2005-2016)

<table>
<thead>
<tr>
<th>Bundle</th>
<th>2005 (n=2,149)</th>
<th>2010 (n=2,654)</th>
<th>2016 (n=1,819)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% of corn farms</td>
<td>% of corn acres</td>
<td>% of corn farms</td>
</tr>
<tr>
<td>Yield monitor (YM) only</td>
<td>0.12</td>
<td>0.14</td>
<td>0.12</td>
</tr>
<tr>
<td>YM + Yield mapping (Ymap)</td>
<td>0.12</td>
<td>0.19</td>
<td>0.21</td>
</tr>
<tr>
<td>YM + GPS guidance (GPS)</td>
<td>0.05</td>
<td>0.11</td>
<td>0.20</td>
</tr>
<tr>
<td>YM + variable rate technology (VRT)</td>
<td>0.05</td>
<td>0.08</td>
<td>0.12</td>
</tr>
<tr>
<td>YM + GPS + VRT</td>
<td>0.01</td>
<td>0.03</td>
<td>0.08</td>
</tr>
<tr>
<td>YM + Ymap + GPS</td>
<td>0.03</td>
<td>0.05</td>
<td>0.13</td>
</tr>
<tr>
<td>YM + Ymap + VRT</td>
<td>0.04</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>YM + Ymap + GPS + VRT</td>
<td>0.01</td>
<td>0.02</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Mean PA technologies adopted (std. error): 0.68 (0.04) 1.29 (0.05) 1.67 (0.06)

Notes: Source: USDA ARMS Phase II for corn 2005, 2010, 2016. Summary statistics represent all corn fields in their respective years using expansion weights provided by USDA NASS. Bundles represent technology packages that include at least the individual technologies. As such, bundles are not mutually exclusive.
The Custom Service Industry’s Role in Precision Agriculture Adoption: A Literature Review

By Scott W. Fausti¹, Bruce Erickson², David E. Clay³, and Sharon A. Clay⁴

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Abstract
This literature review focuses on the role of the precision agriculture (PA) custom services industry in facilitating farmer adoption of PA technology. Based on the review, a series of stylized facts are developed that characterize the custom services industry’s role in the PA adoption process in the United States. The literature suggests that increasing the availability of custom services in local agricultural production markets will positively influence the rate of PA adoption. Recent PA custom services industry field surveys, however, indicate that skilled labor, proficient in PA technology, is critical to develop and provide custom services needed to increase the supply of PA services to farmers. These surveys suggest that currently there is a shortage of qualified labor to work in the PA custom services sector. The PA labor issue appears to pose a potential barrier to the provision of PA technical training desired by customers, and the deployment of PA custom services to customers who have adopted or are considering the adoption of PA technology.

Key Words: Agribusiness, Agricultural Technology, Precision Agriculture, Workforce Development, Retail PA Services Industry

JEL Codes: Q10, Q13, J43, L8

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Introduction

Precision Agriculture (PA) is a generic term that refers to the wide variety of electronic technologies that have been commercially developed over the last quarter century, and specifically adapted for application to agricultural production (Shannon et al. 2018). These technologies can increase production efficiency by providing information on the input requirements and output levels over a heterogenous production space (Davis et al. 1998), which should decrease production cost per unit of yield. Shannon et al. (2018) provides a general overview of this array of technologies. However, PA adoption also increases complexity of the production system as producers move from homogenous to heterogeneous input applications (Aubert et al. 2012).

The commercial adoption of PA technology began at roughly the same time as changes occurred in U.S. agricultural production policy with the passage of the “Federal Agriculture Improvement and Reform Act of 1996,” commonly referred to as the Freedom to Farm Act (McDonald et al. 2013: pp. 22-45; Fausti 2015). During this period, genetically modified organism (GMO) technology-based seed was commercially introduced to American agriculture. The commercial corn-based ethanol industry entered into its industrial growth stage with the passage of U.S. biofuels legislation at the turn of the 21st century (Fausti 2015). Fausti discusses how the convergence of biotechnology innovations combined with changes in U.S. agriculture and energy policy altered the U.S. crop production system. These policies and technological advancements changed producer production practices and allowed producers to pursue increased profit by expanding their production capacity. This lowered the average cost per acre by capturing economy of scale efficiencies and has contributed to farm consolidation in the U.S. row crop industry (McDonald et al. 2013).

The consolidation of farms also opened the door for innovation that transformed the physical capital structure of U.S. farming operations. For example, McDonald et al. (2013: pp. 23-25) reports that in 1970 the average-sized (horsepower) tractor could plant 40 acres per day. By 2010, the average-sized tractor could plant 945 acres per day. McDonald et al. reports that similar production scale effects occurred in harvesting and planting equipment. These production scale effects created an economic incentive to develop complementary technologies to enhance the economies of scale effect in grain and oilseed cropping operations.

These complementary production technologies, as a class, is now referred to as precision agriculture technology (Shannon et al. 2018). The PA adoption issue, and the diffusion of various PA technologies has been extensively discussed in the literature (e.g., Lowenberg-DeBoer 2003; Griffin and Lowenberg-DeBoer 2005; Schimmelpfennig and Ebel 2011; Tey and Brindal 2012; Aubert et al. 2012; and Schimmelpfennig and Ebel 2016). However, the adoption rate across categories of PA applications varies widely. As a result, the PA adoption rate literature suggests that PA adoption has been slow, relative to other technological innovations in agriculture. For example, biofuel technology and crop seed development using GMO technology have become industry standard practice. PA adoption rates, however, are highly dependent on which PA technology category is being discussed (Schimmelpfennig and Ebel 2016; Lowenberg-DeBoer and Erickson 2019). According to this literature, guidance system technology is almost universally used, whereas less than 20% of farms reported using variable rate technology (VRT). Therefore, when discussing PA adoption rates, one cannot take a “one size fits all” approach. In addition, for this review, adoption refers to a producer adding a new PA technology to their production management system.
The literature raises two issues when a farmer considers PA adoption. The first issue is the role management (i.e., the farmer) plays in the decision to adopt PA technology. The second issue is the availability of PA expertise in providing assistance to the farmer in making adoption decisions. In the United States, the retail custom services industry (seed/fertilizer/pesticide dealerships) is the most common source of local expertise needed to effectively navigate the PA adoption process (Erickson et al. 2018). Erickson also notes that recent industry survey results indicate that the custom services industry appears to be having difficulty finding qualified PA workers to fill vacant PA positions.

The objective of the literature review is to discuss the linkage between PA adoption rates and the PA retail custom services industry. A review and analysis of the PA literature allows a set of stylized facts to be drawn and provides a framework for discussion of the linkage among the PA rate of adoption, the PA custom services industry, and PA workforce development.

A Review of Labor and Management Factors Influencing the Diffusion of Precision Agriculture Technology Literature

PA Diffusion Literature
The PA literature has demonstrated that adoption of a variety of PA technologies increases productivity, decreases input costs, and reduces labor inputs (e.g., Lowenberg-DeBoer and Erickson 2019; Griffin et al. 2018; Schimmelpfennig and Ebel 2016; Bora et al. 2012; Tey and Brindal 2012; Griffin and Lowenberg-DeBoer 2005). These studies discuss the role of complexity and management in the PA adoption decision. Decision complexity associated with the adoption process is compounded by the level of investment needed to integrate PA technology into the farmer’s production system. The advisory role played by PA vendors, university and government Extension services, and retail farm service providers, in the adoption decision process by management, has been widely discussed in this branch of the literature. The literature infers that PA custom services are a potentially underutilized management solution to the adoption conundrum.

Robertson et al. (2012) address the issue of adoption rates of VRT for fertilizer application in Australia. They identify the complexity of the decision, (e.g., where, when, how much fertilizer, crop, and cropping system) as a key component influencing the individual producer’s adoption decision and industry wide diffusion of PA technology. Robertson et al. state that, “Adoption of complex technology requires the producer to modify a number of farming practices and the management of those practices,” and they conclude that, “Producers need expert support and training to aid in the adoption process.” Furthermore, Robertson et al. (pp. 194-95) argue that “Application of PA systems by farmers can be hindered by the lack of technical support and training…” Paraphrasing Robertson, he concludes that because of the complexity of a farming system, the site-specific nature of the decisions, the lack of local support, and at times the lack of definitive agronomic research to corroborate decisions, it is not unexpected that VRT technology is lagging in adoption relative to other PA technologies.

Aubert et al. (2012) also concludes that complexity is a key barrier to PA adoption for Canadian farmers. They argue that to increase adoption there is a dual prerequisite of increased compatibility across PA technologies and a need for increased farmer expertise to support integration of PA technologies into production systems. Aubert et al. then discusses the role of PA vendors in the adoption process and concludes that vendors play an important role in the farmer’s adoption decision process.
Fountas et al. (2005) compare the farmer’s experience with precision agriculture in Denmark and the U.S. Eastern Corn Belt. They reported that the role of complexity in the PA adoption process was similar for U.S. and Denmark producers. The authors highlight a steep PA learning curve, and the high cost of PA equipment as barriers to adoption. They also indicate a need for trained PA specialists in both the private and public sectors to facilitate adoption rates. They suggested that the willingness to pay for PA services may be a channel for transferring PA knowledge from experts to inexperienced operators.

Pierpaoli et al. (2013) focus on drivers of adoption and conclude that non-adopters lack skills for implementing PA in their operations and may lack the financial resources to purchase PA equipment. They infer that an opportunity exists to develop PA service firms specializing in the provision of contractual PA custom services. Contracting opportunities would provide non-adopters with option to purchase the technical PA knowledge and the application of PA services without the high fixed cost investment associated with purchasing PA technology (Pierpaoli et al. (2013: p. 67). McBride and Daberkow (2003: p. 24) state that “information from sources such as vendors and professional consultants is shown to be the most important to the potential adopter.”

Tey and Brindal (2012) review 25 studies with a focus on the informational, behavioral, social, and economic aspects of PA adoption. They report that adoption is influenced by a multitude of factors and conclude that adoption decreases with the increasing complexity of a technology. However, the availability of outside advisors can help farmers overcome this barrier.

McBride and Daberkow (2003) report that the producer adoption decision is highly influenced by recommendations provided by crop consultants and retail input suppliers. They contend that areas with higher PA vendor concentrations have higher adoption rates. Shannon et al. (2018) also discuss the relationship between vendor concentration and adoption rates. They remark on the tendency of PA technology adopters to cluster around a service provider. Davis et al. (1998) suggest that farmers should consider using custom services as an alternative to the high fixed cost of capital and the steep management learning curve. With respect to the PA custom services sector, they indicate that service providers need a critical mass of PA adopters to justify the capital fixed cost and additional labor associated with providing PA services. These insights on PA adoption clusters suggest there may be a simultaneity issue.

However, the observed tendency of spatial clustering provides an opportunity for rural economic development initiatives at state and federal levels to incentivize PA technology adoption. Spatial clustering of PA adoption around service providers may provide an economic policy path to promote local PA knowledge spillover. In turn, the spillover effect could address the steep learning curve issue raised by Davis et al. (1998), and by Fountas et al. (2005). Similar policy prescriptions have been proposed in the literature (e.g., McBride and Daberkow 2003).

Schimmelpfennig and Ebel (2011) discuss multiple PA technologies considered to be complementary in the production process. They document a positive relationship between the adoption of yield monitor technology and other more complex PA technologies, such as VRT. They conclude that the future cost structure of PA technologies will likely influence future adoption rates.

Schimmelpfennig (2016) also discusses how PA technology can be complementary and have a positive relationship among PA adoption rates, PA adopter profitability, and farm size. Schimmelpfennig (Table 3) reports that producers farming less than 400 cropland acres have a per acre cost 1.6 to 2.7 times greater than those farming more than 1,200 cropland acres using similar PA and
non-PA custom services. Schimmelpfennig also discusses the relationship between farm size and PA adoption, and reports (p.12; Table 1) producers farming less than 600 cropland acres have adopted various PA technologies at a rate lower than producers farming more than 3,800 cropland acres. He concludes that economies of scale do play a role in the diffusion of PA technologies.

Schimmelpfennig and Ebel (2016) describe a sequential PA adoption process and the associated cost savings from adoption. They investigate the complexity of adopting complementary PA technologies with VRT as the final technology added to the production system. Notably, the number of farming operations adopting multiple technologies is inversely related to the number of PA technologies integrated into the farming operation. They report that highly educated producers using other non-PA technologies, such as GMO seed and soil testing, are more likely to be adopters of complex PA production systems.

The Schimmelpfennig contribution and the Schimmelpfennig and Ebel contributions tie directly to the PA complexity issue. Their findings support the conclusions of Robertson et al. (2012) and Aubert et al. (2012) that complexity, compatibility, economies of scale, and lack of farmer PA expertise pose barriers to PA adoption.

In a recent article by Lowenberg-DeBoer and Erickson (2019), they argue that rate of PA technology diffusion debate fails to see the “forest from the trees” (e.g., looking at the small details leads to missing larger overall issues). They assert that PA contains many tools, and producers select the tool(s) that best fits their farming operation, and some tools may not be needed. Lowenberg-DeBoer and Erickson (2019) discuss the idiosyncratic nature of PA adoption decision. For example, less complex technologies like Global Navigation Satellite Systems used in auto guidance have become standard practice in the United States due to its ease of implementation and its broad application to farming operations. On the other hand, they state that VRT applications have been adopted at a much lower rate. For example, VRT may not be appropriate for smaller fields or where field grade and soil variability are not issues. Their observation is consistent with the complexity hypothesis explanation of PA adoption.

Lowenberg-DeBoer and Erickson (p. 1554) argue that the literature has been focused on barriers to adoption and has not been “particularly useful in explaining or predicting national or regional PA adoption trends.” This comment raises an interesting issue and suggests a need for additional research on this topic. A plausible supposition that would provide an explanation for this “lack of trend” is that the failure to explain regional or national trends in PA adoption may be associated with the variability in the availability of skilled PA workers in local markets.

Fausti et al. (2021) provides empirical support that indicates there is a positive association between the quality of the local PA labor force and farm size (a proxy for economies of scale) at the county level. Given that the supply of PA custom services is dependent on the size of its customer base, and on the availability and competency of the local PA labor force, this suggests that variability in regional PA adoption rates may be related to the variability in average farm size across counties. This discussion is consistent with the empirical work of Daberkow and McBride (1998). They report that larger crop farming operations have a higher probability of being PA adopters than smaller crop farming operations. In addition, they comment on producer demand for PA resources and surmise on page 154 that “such services may not be uniformly accessible.”

The above discussion suggests that custom service providers in counties dominated by small and medium-sized farms have a smaller customer base and have greater difficulty finding qualified
PA labor relative to counties dominated by large scale farming operations. This is a plausible explanation for the lack of trend in the PA adoption rate reported by Lowenberg-DeBoer and Erickson (2019). If average farm size is the factor that explains the “lack of trend”, then is there a policy prescription to address the lack of adoption issue in counties dominated by small and medium-sized farms? Daberkow and McBride (1998) discuss potential policy solutions. However, they qualify their discussion by questioning if it is worth the public expenditure to increase the rate of adoption in low adoption areas. Such a policy would be necessary to increase the presence of PA custom service firms in such areas. In addition, any policy proposed would have to address the issue of PA labor supply.

**The PA Workforce Literature**

The review of the PA literature lays the groundwork for a discussion of a subbranch of the literature which focuses on the PA workforce that supports the retail custom services industry. The ability of PA vendors to provide services to farmers relies on two factors, sustained demand for PA services and the availability of a trained PA workforce.

Kitchen et al. (2002) provides an overview of educational needs of the PA industry. They postulate that one barrier to PA adoption is the lack of well-educated and trained workers in the various areas of PA technology. Kitchen et al. argues that the supply of a well-trained workforce is dependent on the number of education programs offering PA instruction. They go on to make numerous recommendations for improving PA education in the United States.

Expertise in precision agriculture, as outlined by Erickson et. al. (2018), is defined as the **Knowledge, Skills, and Abilities** (KSA) to apply PA technology to agricultural production. The retail custom services industry provides the technology, equipment, and expertise to guide the adoption process.

Erickson et al. (2018) provides an overview of the U.S. PA retail custom services industry’s view of the availability of skilled PA workers based on data collected in a retail dealership survey. In the survey, Erickson et al. asked retailers to rank past interviewees for PA positions on the interviewer’s perception of the candidates’ expertise in ten PA competency areas. This study focused on the relationship between types of PA expertise desired by the retailer, and the retailer’s perception of the availability (or lack thereof) of new hires possessing the desired qualifications. Their survey findings suggest that a skilled PA workforce is not universally available across the retail dealership industry. Another question of interest concerning the PA workforce that was asked by Erickson et al. focused on the view of retail custom service firms with respect to the difficulty in finding qualified applicants. Erickson et al. reports that 60% of retail custom service firms had a difficult (2 to 3 months to fill) or very difficult (more than 3 months) time finding qualified applicants. In addition, approximately 50% of the respondents indicated applicants, even though applying for PA positions, have a low or deficient level of understanding across KSA categories. This lack of available labor may pose a potential barrier to the provision of PA services in locations where PA labor is in short supply.

Erickson et al. (2017; p. 22) also reports on the labor shortage issue and raises the issue of PA labor cost using data from a 2017 CropLife© survey of retail dealerships. They found that the percentage of dealerships surveyed indicating an increase in difficulty finding qualified PA employees rose from 47% in 2015 to 62% in 2017. Furthermore, Erickson et al. reports in the 2017 survey that 40% of the respondents agreed or strongly agreed with this statement: “The cost of employees who can provide precision services is too high for precision ag to be profitable.”
The last study to be discussed looks at the issue of the availability of PA workforce training and development. In a study by Fausti et al. (2018) on education institutions with PA offerings, Fausti found a divergence in the educator versus industry expectations of student preparation in KSA areas. For instance, they report statistical means tests for the occupational category of equipment operator that indicate educational institutions gave 8 of 10 KSA categories a higher importance ranking than retail dealership respondents. In turn, retail dealership respondents rank math and statistical skills higher than educational institutions across occupation categories (Fausti et al. 2018: Table 3). This divergence may be a partial explanation for the custom service industry’s view that the PA labor pool lacks qualified candidates for PA positions in the industry. When one considers the findings in the studies discussed above, it suggests that the Kitchen et al. (2002) recommendations for developing curriculum, to turn out well-educated and trained workers in the various areas of PA technology, is still a work in progress.5

**Literature Summary**

The literature cited provides a series of common themes tying the rate of PA technology adoption to the ability of farmers to make the adoption decision. Commonly cited factors that pose potential barriers to adoption are: a) the complexity issue of adopting PA technology; b) lack of farmer expertise to identify PA technology suited for their farming operation and the lack of management skills to oversee a PA system once adopted; and c) the cost of adoption (both fixed and variable cost). The literature also identifies a set of potential solutions to overcome these barriers: a) PA expert services (consultants and Extension services) can function as a facilitator of farmer education programming to overcome the lack of farmer PA expertise; and b) farmer contracting for PA services through local retail agricultural custom service dealerships.

The literature has identified the custom services industry as a potential solution option to the rate of adoption issue. Evidence suggests that there is a linkage between custom services availability and adoption. This linkage is more relevant for small to medium-sized farming operations. The PA labor force education literature indicates that there is a shortage of qualified workers to meet the demand by the retail dealership industry in the United States. Thus, the rate of adoption for small and medium-sized farms is tied to the expansion of affordable custom services, and the expansion of custom services is tied to the size of a qualified PA labor pool. By extension, the shortage of qualified PA labor may be a partial explanation for differences in the cost per acre for custom services between large vs. small farms reported by Schimmelpfennig (2016). In turn, the cost differential combined with the positive association between average farm size and ability of custom PA service firms to find qualified PA labor (Fausti et al. 2021) provides a potential answer to the issue raised by Lowenberg-DeBoer and Erickson (2019) for the lack of a trend in the PA adoption rate at the regional or national level.

When the literature is viewed from this vantage point, it implies that there is a linkage among the literature issues of the PA adoption decision, PA custom services availability, and PA workforce development. This linkage allows a set of stylized facts to be drawn from the literature.

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5 Programs have been expanding. For example, South Dakota State University offers major & minor, North Dakota State University is developing a major. Kansas State University and the University of Missouri both have certificate PA programs.
Adoption Decision

- PA adoption increases farm management complexity.
- PA adoption requires a substantial fixed cost investment by producers who purchase PA equipment. Variable cost associated with PA implementation (purchase or contract) is dependent on economies of scale.
- Adoption of multiple PA complementary technologies increases production efficiency, and the benefits increase as production scale increases; however, complexity increases.
- Farm size, profitability, and PA adoption rates are positively related.
- Lacking economies of scale, small and medium-sized farming operations are at a cost disadvantage that may pose a barrier to PA adoption.

Custom Services

- Custom PA services are an alternative adoption option to purchasing PA equipment.
- Custom service firms provide PA expertise to overcome the complexity issue for producers who own PA systems or contract for PA production and management services.
- Economies of scale and cost per acre of custom PA services are inversely related.
- PA adopters tend to cluster around custom PA service providers.
- Custom PA service providers establish operation centers in areas where the PA adoption level supports the investment.
- The retail custom services industry reports a shortage of qualified trained workers.
- PA labor cost is affecting the profitability of custom services provision.
- A well-trained PA workforce is necessary for the retail custom services industry to support future expansion of PA adoption.

Conclusion

These stylized facts suggest that complexity and the lack of producer expertise are factors that do affect adoption rates. In turn, the literature implies that if farmers had access to PA Extension services and affordable PA vendor expertise, then adoption rates would be higher. However, greater access implies an increase in supply of custom PA services in local markets. PA service providers need a critical mass of PA adopters to set up operations in a local market. In turn, an increase in the supply of PA services will result in an increase in demand for PA skilled labor in local markets. Recent survey work indicates that the custom services industry is having a difficult time hiring qualified PA labor. It appears that the conditions necessary for the custom services industry to support the expansion of producer adoption of PA technology will require the development of policy that simultaneously incentivizes producer adoption and increases the supply of the qualified PA workers. Further research on these issues is needed.
References


Is the Custom Service Industry’s Role in Precision Agriculture Linked to Workforce Development?

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Abstract
Retail dealership survey data suggests that the lack of a qualified precision agriculture (PA) workforce limits the ability of the PA service industry to provide technological knowledge and services to producers who have adopted PA technology. The key empirical findings suggest that retail dealerships have the greatest difficulty finding workers who have, a) the capability to operate and collect data using specialized PA technology, b) the capability to interpret and develop management strategies using PA generated data, and c) a basic generalized competency in PA technology and its applications. The perceived shortage of skilled workers suggests that there is a need to expand the PA workforce with individuals who have knowledge, skills, and abilities (KSAs). A PA qualified workforce is necessary to provide support for the provision of PA services to current users of PA technology and new PA adopters.

Introduction
The role of labor in agriculture is a long-standing issue of interest to agricultural economists. One issue of consequence discussed in this literature is the linkage among technology innovation in agriculture, the adoption rate of technology, and workforce development (Lambert 2018). The issue of workforce development and labor skill competencies has been an area of research interest in the agricultural education literature (e.g., Colelasure 2020; Osman and Murdad 2020; Easterly et. al., 2017). These studies draw from the human capital literature as a theoretical framework for their empirical survey work using empirical methods like Delphi panels to elicit preferences from industry

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These studies focus on skill requirements and student characteristics that are in demand by employers of agricultural workers.

Workforce development to support the adoption of precision agriculture (PA) is a topic gaining greater attention within this literature. Kitchen et al. (2002) first raised the issue of PA workforce development. They argued that the PA adoption was encumbered by the lack of well-educated and trained workers in various PA technology areas. They stated that workforce development will be dependent on the number of educational institutions offering PA educational programing.

Erickson et al. (2018) conducted a workforce survey in 2015 of the PA retail services industry and asked dealership management to rank current and potential employees based on PA KSA categories. Erickson et al. reported that survey respondents had a difficult time finding qualified PA workers. In 2017, Erickson et al. (2017) conducted a generalized PA custom services survey of retail dealerships. In this survey, 62% of respondents in 2017 indicate that there is a lack of qualified PA workers (Erickson et al. p.22: figure 28). This represents an increase of 15% in two years. Additionally, 40% of respondents reported that the cost of PA labor was too high and made offering PA retail services unprofitable. This response category was 28% in 2015 (Erickson et al. p.22: figure 27). The reported findings of the two Erickson surveys indicate the retail dealership industry faces a persistent labor issue.

Fausti et al. (2018) conducted a survey of educational institutions in 2015. The survey focused on PA curriculum, collecting information on PA classes, certificates, or degrees offered by institutions. Fausti et al. (2018) compared the educator survey results to Erickson’s 2015 PA workforce survey of the PA custom services industry. Data from the two surveys indicated that there is a divergence between what educators see as a high priority in PA training programs, as compared to the essential KSA training expected by firms in the custom services industry. From this study, one can conclude that there is a potential divergence in educator perceptions versus workforce realities. The Fausti et al. study provides a partial explanation for the shortage of skilled PA labor reported by Erickson et al. (2017 and 2018).

Lowenberg-DeBoer and Erickson (2019; p. 1554) look at the PA adoption debate in the PA literature, commenting that the literature has not been “particularly useful in explaining or predicting national or regional PA adoption trends.” Within this adoption literature, Fausti et al. (2021), argues that the adoption issue is partially a function, or lack, of PA workforce development. Fausti et al. suggest that the failure to explain regional or national trends in PA adoption is linked to the variability in workforce development at the local and regional level.

The data collected from the 2015 workforce survey of PA retail dealerships (Erickson et al. 2018) were acquired. The data provide a unique opportunity to: a) identify specific KSA skill areas that survey respondents associate with inadequately trained PA workers; b) identify the relationship between retailer perception concerning the difficulty of hiring qualified PA workers and retailer perception of worker knowledge of PA technology and applications; and c) determine if county-level

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5 Erickson et. al. (2018), outlines the concept of expertise in precision agriculture, and defines expertise as Knowledge, Skills, and Abilities (KSA) applicable to PA technology to agricultural production.
farm size (economies of scale proxy) is linked to workforce development (labor availability and quality) issues facing the retail dealership industry.

**Precision Agriculture Retail Dealership Survey Instrument and Data**

Erickson et al. (2018) developed a survey instrument to elicit the perceptions of PA retail dealerships on the quality of educational training in local PA labor pools of skilled workers for which PA retail dealerships were competing. The survey subject pool was drawn from email lists provided by CropLife magazine, a publication of Meister Media, and the Certified Crop Adviser program. The questionnaire was emailed during the summer of 2015. Erickson et al. (2018: p.6) indicated that the contact list contained approximately 10,000 email addresses. They did raise one caveat concerning the nature of the organizations providing the email lists: “likely more reflective of crop protection, seed, and fertilizer retailers and consultants as opposed to others that may be offering precision services such as farm equipment dealers, farmers, or farm managers.” Erickson et al. reported a total of 172 usable responses.

The Erickson et al. (2018) survey collected data on PA occupation categories and on KSA categories. Erickson et al. identify the following occupational categories for PA service workers; 1) Equipment Operator, 2) Agronomist, 3) Precision Equipment Technician, 4) Technical Support, and 5) Precision Sales Specialist. The following ten PA KSA categories were identified: 1) Ability to make effective agronomy recommendations; 2) General knowledge of PA technology; 3) Ability to produce accurate digital maps of fields using spatial information within specialized software; 4) Ability to operate PA equipment (monitors, controllers, etc.); 5) Ability to install and repair PA hardware and equipment, including calibration and troubleshooting; 6) Operational knowledge of computer spreadsheet applications to record and analyze agricultural field data; 7) Effective written and verbal communication skills within PA activities; 8) Working understanding of statistical standards to produce means and standard deviations; 9) Operational knowledge of basic business and accounting principles; and 10) Operational knowledge of PA software (database query, interface, and mapping).

**Survey Data and Data Transformation**

Retail dealership survey and data were provided by Erickson et al. (2018) to the authors. Subject responses for the following retail dealership survey questions were selected for discussion and analysis: a) Q1-zipcode identifying respondent location; b) Q7-level of difficulty finding qualified applicants for PA positions by occupational category; c) Q8- dealership ranking of PA knowledge of interviewees (past two years) across all ten KSA areas; and d) Q9-dealership ranking of importance of specific KSA areas across occupational categories for open positions in their firm.

Survey questions 7, 8, and 9 are Likert Scale qualitative responses. Boone and Boone (2012) provide a discussion on how to evaluate Likert vs. Likert-type question formats. According to Boone and Boone (p. 2) “A Likert Scale… is composed of a series of four or more Likert-type items that are combined into a single composite score/variable during the data analysis process. Combined, the items are used to provide a quantitative measure of a characteristic or personality trait.”

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6 The survey referenced is a unique workforce survey conducted using the CropLife database. Traditionally, CropLife surveys focus on PA technologies being offered by the retail dealership industry. Boehlje and Langemeier (2021) provide a discussion of CropLife survey data. The usual caveats apply (Smith, 1983) to a non-stratified non-random sampling procedure (e.g., self-selection bias by respondents, non-representative sample of institutions selected for the survey).
questions 7, 8, and 9 are each aggregated into a single composite variable in a manner consistent with the recommendation of Boone and Boone.

Question 7 provides the data on the question being addressed in this paper (Is there a shortage of qualified PA labor?). The data are represented by the variable PALABOR, and the variable reflects dealership responses to question 7. The subject’s Likert Scale response for each occupational category were summed. The difficulty of finding qualified PA workers ranked from 1 = no shortage to 5 = no qualified workers in the local labor pool (area). This Likert Index has a range from 5 (no labor shortage across the five occupational categories) to 25 (no qualified PA workers averaged across the five occupational categories).

In the case of question 8, an index of KSA general competencies is constructed by aggregating retail dealer Likert Scale rankings of the ten PA KSAs for interviewees applying for PA positions in the prior two years and is labeled KSAGEN. Question 8 rankings range from 1 to 4. The KSA qualified PA workers ranked from 1 = deficient KSA knowledge, to 4 = highly qualified KSA workers in the local labor pool (area). Therefore, the Likert Index ranges from 10 to 40. An index value of 10 indicates that the applicant’s level of PA knowledge is deficient. A ranking of 40 indicates a high level of knowledge across all 10 KSA areas. It is hypothesized that the Likert Scale Index for Q8 will have an inverse relationship with the Likert Scale Index for Question 7. The higher a dealership ranks interviewees on KSA qualifications, the less difficult it is for that dealership to find qualified PA workers.

Question 9 asks retail dealerships to place a ranking of 1 (least important) to 3 (most important) for each KSA by each occupational category when the dealership is screening new employees for PA positions. As a result of how the question is structured, a Likert Scale KSA index is constructed for each KSA across occupation category. Each KSA index has a range of 5 to 15 and is a quantitative measure of the retail dealership’s view on the importance of an interviewee’s level of competency for each KSA area. An index value of 5 indicates that for a particular KSA category across the five occupational areas, this KSA competency is not important. An index value of 15 indicates that this particular KSA-specific competency is the most important (averaged across the five occupational categories). It is hypothesized that the ten KSA Likert Scale Index variables (KSA1 to KSA10) which are constructed from Q9 will have a positive relationship with the Likert Scale Index for Question 7. These hypothesized relationships are based on the PA labor force literature supposition that the lack of KSA training has resulted in a lack of qualified PA workers in local labor markets.

Non-Survey Data
The research team collected USDA data on county-level economic variables that are hypothesized to affect the demand for PA services in the county where the retail dealership resides (USDA 2017). It is assumed that county-level median and average farm acreage statistics did not change significantly from 2015 when the Retail dealership survey was conducted and the reported values for those variables in the 2017 Ag Census.

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7 In the Erickson et al. (2018) manuscript, a copy of the survey instrument is provided. Respondents answered question 9 as 1=most important, and 3=least important. For this study, the rankings are reversed from the original instrument: 1=least important and 3=most important.
8 It is assumed that county-level median and average farm acreage statistics did not change significantly from 2015 when the Retail dealership survey was conducted and the reported values for those variables in the 2017 Ag Census.
average farm acreage minus the median farm acreage (Skew) in the county where the retail dealership resides. The second proxy variable is average farm sales (Avgsales). Avgsales is defined as total farm sales in a county divided by the total number of farms in the county. They are a proxy for skewness with respect to farm size in a county. It is hypothesized that these proxy variables will capture the relationship between county-level economies of scale of agricultural operations and retail dealership views of PA labor issues. Schimmelpfennig (2016) provides empirical evidence that indicates a positive relationship between farm size and PA adoption rates.

Positive skewness indicates large-scale farming operations dominate agricultural production in the county where the dealership is located. Negative skewness indicates small-scale farming operations dominate agricultural production in the county. Given the empirical evidence provided in the literature on the relationship between farm size and adoption rates (e.g., Schimmelpfennig 2016), the demand for custom PA services will be higher in counties dominated by large farming operations. Schimmelpfennig and Ebel (2016) report that producers who adopt multiple PA technologies tend to operate larger farms and incorporate other modern technologies such as GMO seed and soil testing. This suggests PA custom service firms providing PA services to sophisticated PA adopters require a high-quality workforce. Based on this discussion, it is hypothesized that county-level scale economies are associated with PA retail dealership perceptions of PA labor availability and quality.

Data Source and Scope
Complete survey responses across ten KSA’s queries for question 9 varied between 64 and 66 observations. Complete responses for question 7 totaled 102, and question 8 totaled 96. The Skewness questions totaled 101. As a result of incomplete subject responses to questions, the data set used in the empirical analysis discussed below contains various total observations for questions used in the correlation analysis. Figure 1 provides a graphical depiction of the 102 observation locations that are identified by zip code (survey data).

Empirical Methodology and Results
The Likert Indices data are ordinal. Therefore, Spearman Correlation Analysis (Newbold et al. 2013) was selected to evaluate the statistical associations between PALABOR, KSAGEN, SKEW, and the ten KSA variables constructed from question 9 in the survey. Spearman Correlation estimates for PALABOR, KSAGEN, SKEW, and KSA2, KSA3, KSA4, KSA6, and KSA8 are reported in Table 1 (see bottom of page 71 for KSA definitions). Please note that correlation does not imply causation.

\[^9\] A common empirical measure for skewness (defined as the 3rd moment of the probability density function) is the Pearson’s second skewness coefficient (median skewness) or Pearson 2 measure of skewness (Doane and Seward 2011). It is defined as: \(3 \times \frac{\text{mean} - \text{median}}{\text{StdDeviation}}\). It is assumed here that the mean minus the median provides a rough measure of the distribution of acres operated in a county and relative farm size. Data on the standard deviation are not available. It is assumed that farm sales are positively correlated to farm size and farm size is correlated with scale economies. A positive skewness proxy value implies that large farms dominate acres operated in a county. We view this as an indication of an economies of scale effect that is affecting the distribution of acres operated in a county by farm size.
Statistical Results

Correlation analyses (Table 1) indicate a negative association between PALABOR and KSAGEN.\(^\text{11}\) The negative statistical association indicates a retailer dealership finds it more difficult to find qualified PA applicants as the level of retail dealer assessed KSA knowledge of interviewees declines. This implies that the lack of trained PA labor is contributing to the PA labor shortage. The statistical association between SKEW and Avgsale with PALABOR is negative, and the statistical association between KSAGEN and Avgsale is positive. This suggests that as county’s average scale economies increases, local PA dealerships have less difficulty finding qualified PA workers. This is an interesting correlation. It implies that dealerships with farming operations with smaller scale economies in their county will have greater difficulty finding qualified PA workers. For those dealerships, their customer base would contain a higher proportion of small farms relative to dealerships in counties with greater scale economies.

Given the literature discussion, economies of scale appear to be a factor associated with PA labor supply (Fausti et al. 2021). This implies custom service firms operating in counties with a preponderance of small and medium-sized farms will have a greater difficulty providing PA services, and this would have a negative effect on PA adoption rates in those counties. This discussion provides a plausible explanation for the Lowenberg-DeBoer and Erickson (2019) query concerning the lack of trend in the PA adoption data. PA labor supply is positively associated with average scale

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\(^{10}\) Regression analysis was initially selected as the statistical tool for data analysis. However, during the regression diagnostic evaluation of regression models, endogeneity was found to be an issue for models containing PALABOR, KSAGEN, and KSA2. A search for appropriate instrument variables to resolve the problem was unsuccessful.

\(^{11}\) The caveat of the non-random sampling selection process used in the retail dealership survey may be subject to self-selection bias and implies that the results of the empirical findings are valid for the sample only. The data are non-normal and so Spearman Correlation analysis was used (Newbold et. al. 2013).
economies, and it appears that average scale economies play a role in determining county or regional adoption rates.

The KSA variable KSA2 provides a ranking of the importance a dealership places on the level of “Knowledge of Precision Agriculture Technology” for potential new employees averaged across all five occupation areas. KSA2 is positively correlated with Avgsale, KSAGEN, and SKEW (Table 1). Scale economies appear to be associated with a dealership’s desire for new employees to have a strong general knowledge base of PA technology in counties with greater scale economies relative to counties with lesser scale economies. The positive statistical association between KSAGEN and KSA2 suggests that those dealerships which value a high level of general PA knowledge will rate those interviewees higher with respect to their level of overall KSA training. This suggests that PA educational curriculum needs to provide students with a comprehensive general education course in PA application and technology that is scaffolded into more advanced PA courses.

The last issue to be addressed is how dealerships view the importance of a specific PA knowledge (KSA) area for potential new employees with respect to the dealership’s view on the level of difficulty of finding qualified PA workers to hire. Correlation analysis finds that four KSAs (3, 4, 6, and 8) are statistically significant and positively correlated to PALABOR (Table 1). This suggests the higher the ranked importance of these four KSA areas, the more difficult retail dealerships perceive hiring qualified PA workers.

KSA areas 3 and 4 involve using specialized PA equipment and providing production management information upon which PA management decisions will be based. KSA areas 6 and 8 denote the skill set necessary to interpret and apply the information generated by KSA areas 3 and 4. The empirical results suggest that key focus areas of PA education initiatives should be on the development of curriculum which directly support KSA areas 3, 4, 6, and 8. These conclusions, based on correlation analysis, are consistent with the discussion provided by Erickson et al. (2018). One final comment on KSA 8, correlation analysis indicates a negative association with SKEW and Avgsale. This suggests dealerships located in counties lacking scale economies have a greater need for workers with statistical skills.

Conclusion

Non-random survey data was used to empirically test whether there is evidence to support the supposition that PA workforce constraints are associated with the ability of the retail services industry to supply PA custom services. Preliminary empirical evidence presented implies that a lack of KSA training in the specific skill areas is perceived as an issue by the PA retail services industry. These KSA areas include the ability to operate PA equipment, generate PA map and data output, analyze PA data, and interpret statistical PA output. These particular skills are associated with the perception held by custom service operators as areas where there is a lack of qualified PA labor needed to meet the labor requirements of the industry.

The key findings suggest that retail dealerships have the greatest difficulty finding workers who have the following KSA skills: a) the capability to operate and collect data using specialized PA technology; b) the capability to interpret and develop management strategies using PA-generated data; and c) a basic generalized competency in PA technology and its applications. These are the PA educational curriculum areas the retail dealership industry associates with their perception that there is a lack of skilled PA workers in local labor pools. We suggest that PA educational curriculum needs
to provide students with a comprehensive general education course in PA application and technology that is scaffolded into the more advanced PA courses which focus on the application of PA technology and how the information from applications is integrated into a farmer’s production management plan.

Also note that empirical evidence suggests that farm size within a marketing area (county) where the retail dealership resides is associated with the dealership’s access to qualified labor. This suggests that those dealerships which reside in counties with greater scale economies have less difficulty finding skilled PA workers. This implies that in counties where small and medium-sized farms represent the majority of farm type, producers may have greater difficulty finding PA custom services to act as a guide during the PA adoption process.

To answer the question inferred by the title of the paper, “Is the Custom Service Industry’s Role in Precision Agriculture Linked to Workforce Development?”, survey results suggest the availability of qualified PA workers is a constraint on the PA retail dealership industry’s ability to provide PA services to current and potential adopters of PA technology. The literature suggests that the current structure of PA education in the United States is a contributing factor to that constraint.
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Challenges, Opportunities, and the Way Forward for the U.S. Hemp Industry

By Sunil P. Dhoubadel

Abstract

The passage of the 2014 and 2018 Farm Bills generated unprecedented enthusiasm in the U.S. hemp industry. We conduct a comprehensive assessment to identify the challenges and opportunities of this growing industry. The findings indicate that although there is considerable enthusiasm for the hemp industry, there are many challenges that the industry needs to overcome to survive and establish itself. It will require a concerted effort to mitigate the risk and grow the industry. We point out some specific actions that would be helpful for the development of the U.S. hemp industry.

Keywords: U.S. hemp industry, hemp policy, 2018 Farm Bill, Cannabinol (CBD), hemp products, Tetrahydrocannabinol (THC)

JEL Classification: Q18, Q13

The 2014 and 2018 Farm Bills provided a legal foundation for industrial hemp cultivation and generated unprecedented enthusiasm in the U.S. hemp industry. Soon after the 2014 Farm Bill, Colorado, Indiana, Kentucky, and Vermont allowed hemp cultivation under their state pilot programs (Mark et al., 2020). The pilot programs quickly reached 15 states by 2016, and by 2020, 47 states legalized hemp farming (Vote hemp, 2017 and Drotleff, 2020).

Given the enormous interest surrounding the U.S. hemp industry, it is crucial to evaluate its potential and shortcomings to identify future interventions and policy aids. In this article, we discuss the status of the U.S. hemp industry and conduct a comprehensive assessment to identify challenges and opportunities to this industry. Based on the assessment, we point out some policy actions to directly address the challenges and opportunities of the U.S. hemp industry.

The U.S. Hemp Policy and Hemp Industry

The 1937 Marijuana Tax Act is the first law enacted to discourage hemp production by imposing tax and requiring producers of Cannabis sativa species to apply for the license (USDA AMS, 2019). After the passage of the 1970 Controlled Substance Act, which regarded hemp as 'Marijuana,' a controlled substance, its production was prohibited for several years (Malone and Gomez, 2019; Vote Hemp, 2020). The Agricultural Act of 2014 (2014 Farm Bill) allowed higher education institutions and the state departments of agriculture to cultivate and research hemp under state pilot programs (USDA AMS, 2019). The bill still prohibited independent cultivation of hemp beyond the state pilot.

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programs. However, the 2018 Farm Bill legalized industrial hemp farming. The bill distinguished hemp from marijuana by defining it as the variety of *Cannabis sativa* L. with Cannabinoid delta-9 tetrahydrocannabinol (THC) concentration not greater than 0.3% on a dry weight basis. The bill effectively transformed hemp from a controlled substance to a new agricultural crop and allowed commercial production of hemp. The cultivation of hemp with a THC concentration above 0.3% is still prohibited under the law (USDA AMS, 2019). Based on the 2018 Farm Bill, the USDA has recently published the final rule that governs domestic hemp production in the United States (USDA AMS, 2021).

U.S. hemp cultivation significantly increased once states began issuing licenses under pilot programs and the state hemp programs. Between 2016 and 2019, the number of hemp licenses issued by the states increased by almost 1,965% and planted acres by 2,284% (Table 1). The sales of hemp products also grew from $85 million in 2015 (Hemp Business Journal, 2016) to $820 million in 2017 and are projected to reach $1.9 billion by 2022 (Hemp Business Journal, 2018). The hemp industry’s growth led to a drastic decrease of 57% in U.S. hemp seed imports between 2016 and 2017 (Hemp Business Journal, 2018). The recent data on planted and licensed acres for hemp suggest that Colorado, Kentucky, Montana, and Tennessee are the major U.S. hemp-producing states (Table 2). Colorado has gone a step further, implementing hemp-focused programs such as the Colorado Hemp Advancement Management Plan (CHAMP) to promote its hemp industry (Hill et al., 2020).

The hemp industry’s growth is mainly attributed to the Cannabidiol (CBD) demand, which is allegedly claimed to be effective in treating epilepsy, insomnia, and chronic pain (Grinspoon, 2020). However, so far, the Federal Drug Administration (FDA) has approved Epidiolex, which contains a purified form of CBD for the treatment of seizures (FDA, 2021). CBD is mainly extracted from hemp flowers. The utilization of other hemp plant parts such as hemp seed and hemp fiber is growing. The FDA has issued "generally recognized as safe" notices for hemp seed-derived food ingredients such as hulled hemp seed, hemp seed powder, and hemp seed oil (FDA, 2021). Hemp seed can be consumed as food in granola and cereals or processed into hemp seed oil. Hemp seed is considered to have high nutritional value because of the high amount of Omega 3 and Omega 6 fatty acids, vitamin E, and protein (Small and Marcus, 2002). Hemp oil is used as cooking oil, salad oil, and in the production of industrial products, including lubricants, oil paints, varnishes, and personal hygiene products such as soap, shampoo, and cosmetics (Allen and Whitney, 2019). Hemp fibers extracted from hemp stalk and leaves are used in producing paper, industrial textiles (e.g., ropes, nets, carpets), consumer textiles, and animal bedding materials (Allen and Whitney, 2019).

Hemp Business Journal (2018) reports that in 2017, the United States sold $820 million hemp-

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2 In this paper, hemp farming or the U.S. hemp industry refers to the production or marketing of hemp that satisfies the statutory definition of hemp as defined in the 2018 Farm Bill. The bill defines hemp as “the plant species *Cannabis sativa* L. and any part of that plant, including the seeds thereof and all derivatives, extracts, cannabinoids, isomers, acids, salts, and salts of isomers, whether growing or not, with a delta-9 tetrahydrocannabinol concentration of not more than 0.3 percent on a dry weight basis” (USDA AMS, 2019). The term industrial hemp is used interchangeably with the legal hemp in the paper.

3 It is worth noting that this is the case even in states where marijuana is legal. A grower cannot grow marijuana under a hemp license.

4 Because the planted acre data for Oregon are not available, we did not include Oregon in the list, but based on licensed acres data reported by Stelton-Holtmeier et al. (2021) for 2019 (51,313 acres) and 2020 (27,434 acres), Oregon is also one of the major states for hemp.
based products consisting of 23% ($190 million) of CBD products, 22% ($181 million) of personal care
products, 18% ($144 million) of industrial products, 17% ($137 million) of food products, and 20% ($166 million) of other consumer products and textiles, and supplements. They also project sales of hemp-based products to reach $1.9 billion by 2022, with a 34% ($646 million) share of hemp-derived CBD sales.

**Challenges**

Although the number of hemp planting licenses issued by the states increased by 27% between 2019 and 2020, planted acres decreased by 31% in that period (Table 1). In addition, the prices of Cannabinoid biomass dropped by 83% between 2015 and 2020 (Yahn-Grode, 2020). Most recently, the price of Kentucky hemp biomass fell from $4.35 per percent of CBD content per lb. to $0.74, a drop of nearly 83% between July 2019 and January 2020 (Yahn-Grode, 2020). Last year, two high-profile U.S. hemp companies based in Kentucky – GenCanna Global and Sustrand, LLC filed for bankruptcy (Grode, 2020). Between April 2019 and March 2020, the publicly traded American Cannabis Operator Index, which includes companies producing industrial hemp products, dropped by 86% (New Cannabis Ventures, 2021). This indicates a volatile hemp market, as predicted by Sterns (2019).

The drop in hemp prices and bankruptcies of hemp companies indicate a challenging time ahead for the relatively young industry. The industry may not be viable in the future if it fails to grow. We highlight below some of the challenges associated with this industry.

**Niche market status and the problem of excess supply:** The current hemp market is a niche market at best. The current market size is still very small compared to other agricultural markets. For example, per PanXchange estimates, the entire U.S. cannabinoid market would require only 2,819 acres of hemp, which is about 4.4% of the 2020 hemp acreage reported by the USDA Farm Service Agency (PanXchange, 2020). About 85% of U.S. hemp acreage in 2020 was intended for the CBD market (Yah-Grode et al., 2021), indicating an alarming gap between hemp demand and the planned supply. The gap can potentially further decrease the raw biomass price and the prices of CBD products in the future. The downward spiral of hemp prices will continue until the increased demand matches the excess supply. It is not clear how long it will take to get to that equilibrium point.

**Lack of well-established production technologies:** Given that hemp is a new agricultural crop, its production-technology is not well established. Little information is available to U.S. hemp farmers regarding seeds, seeding rate, fertilization, pests and pesticides, and other cultural practices that would be suitable for their farm conditions (Mark et al., 2020 and Allen and Whitney, 2019). Some states have certified hemp seeds, but there are no certified seeds for most hemp-producing states or at the national level. Besides, no harvesting equipment is designed specifically for hemp, and most hemp is harvested manually (Yah-Grode et al., 2021). There is no recommended post-harvest technology for various uses of hemp biomass.

The 2018 Farm Bill explicitly mandates that hemp biomass for CBD extraction cannot exceed 0.3% THC level. The seed and production practices suitable in one region of the country producing biomass with less than 0.3% THC do not guarantee that it will have the same result in other parts of the country with different climatic and soil conditions. The lack of region-specific certified seeds
increases the risk to hemp farmers compared to other farmers. Besides worrying about the production and productivity of their hemp crop, they need to be concerned about the THC level of the produce. Failure to be within the 0.3% THC level means they have to destroy their crop and forego the season's revenue with an additional cost to destroy the crop.

Lack of production management and market information: New hemp producers and processors who want to run a profitable enterprise need to understand production costs and markets clearly to make their business decisions properly. Such business information from public and private sources are minimal (Raszap Skorbiansky et al., 2021). Therefore, it is hard to make projections or to form price expectations.

It is crucial to know the expected revenue and costs of hemp farming to a new hemp producer. There are a few representative hemp budgets available (e.g., Mark and Shepherd, 2020 (for Kentucky); Hanchar, 2019 (for New York); Harper et al., 2018 (for Pennsylvania), but these budgets show quite a variability in returns from hemp production (Tables 3, 4, and 5) and are specific to the eastern/northeastern region of the United States. For example, Kentucky's estimated hemp seed production return is $-166/acre, while New York and Pennsylvania are $624 and $546, respectively; a range of nearly $800/acre (Table 3). Similar patterns are observed in the case of fiber and CBD budgets (Tables 4 and 5). The CBD budgets in Table 5 show a possibility of $3,343/acre net return in Kentucky, but a loss of $1,432/acre in Tennessee, again a range of $4,775/acre between two budgets. Given the variability in the budgets, it isn't easy for a new farmer to realistically estimate expected returns from hemp farming and decide to start hemp farming.

There seems to be no consensus regarding the hemp industry's outlook. For example, two prominent hemp business information publications, Hemp Industry Daily and Hemp Business Journal differ in industry growth projections. Hemp Industry Daily (2019) projects U.S. CBD sales to be $5.6-$6.8 billion by 2022, which is almost nine times higher than the $646 million projected by Hemp Business Journal (2018). According to the Hemp Business Journal, sales of all hemp-based products are projected to be no more than $1.9 billion. Given the two contrasting scenarios, it is difficult to gauge how the U.S. hemp market will evolve in the future. Also, most of the growth projections are based on assumed growth in CBD use, the primary hemp product. However, the claimed benefits of CBD products are not yet scientifically verified, which will affect future growth. Given this scenario, it is not realistic to assume widespread use of CBD for medical and food purposes soon, adding another layer of risk to the industry.

Lack of access to market, marketing institutions, and quality standards: There is a lack of established market and marketing channels for the U.S. hemp industry. There is no established spot or cash markets. Forward contracts between producers and processors are rare (Mark et al., 2020). When forward contracts are available, they leave hemp product prices flexible, defeating the purpose of a forward contract to minimize price risks (Raszap Skorbiansky et al., 2021). There are no established marketing channels that link hemp producers with the processors, wholesalers, and retailers and facilitate the flow of hemp products from farms to ultimate consumers. Given the lack of proper market and marketing infrastructures, it is estimated that only 25-33% of hemp output makes it to the market (Allen and Whitney, 2019).

5 For example, Lee et al. (2020) explain the impact of marketing channels on farm profitability in Taiwan.
Processing is an essential part of the hemp industry, but very little is known about hemp processors’ location and capacities in various states. According to Allen and Whitney (2019) estimates, the U.S. hemp processing capacity is very small to process hemp produced in the country on time. One processor in the United States handles about 100 acres of hemp harvest or about 200,000 lbs. of biomass. Processing the entire output takes on average one to three years, depending upon the type of technology used in processing. As a result, there is significant uncertainty regarding timely hemp processing. Besides inadequate processing capacity, there is no standardization and quality control of processed hemp products. For example, there have been instances of false claims regarding the CBD content of the CBD oil sold in the U.S. market (Allen and Whitney, 2019).

**Lack of clarity on the policy for regulating hemp products:** The most significant driver of hemp demand is the potential use of hemp-derived CBD for medical and food/food supplement purposes. The 2018 Farm Bill provisions are limited to hemp farming only, and the USDA does not regulate the food and drug uses of CBD as it falls under the purview of the FDA (USDA AMS, 2019). The FDA has yet to provide clear-cut guidance regarding CBD regulations for medical and food/food supplement purposes. For the FDA to issue any regulations regarding CBD use, it will first look into all the scientific evidence regarding claimed health benefits and its side effects. Given the lengthy process, there is a significant delay in the formulation of the hemp policy by the FDA (Hemp Industrial Daily, 2021a). If the FDA determines that CBD use does not have the claimed health benefits or, worse, is detrimental to human health, it will negatively impact the U.S. hemp industry. Given the lack of an FDA policy on CBD use, this constitutes the most significant uncertainty regarding the future demand and growth potential for CBD. The negative effect of policy uncertainty on business investment is well documented in the literature (e.g., Gulen and Ion, 2016; Dixit and Pindyck, 1994; Rodrik, 1991 and Bernanke, 1983). The FDA policy uncertainty means that new firms will take time to enter the industry, and existing firms will be hesitant to expand their business.

**Import competition:** Besides the domestic factors, the established players in the world hemp market, including Canada, Europe, and China, provide competition to the domestic hemp industry (Mark et al., 2020). According to Hemp Industrial Daily (2021b), "non-CBD imports into the United States grew by 10% in the first ten months of 2020, compared to the same period in 2019." Table 6 shows that the six-year average value (from 2016-November 2020) of various hemp products imported in the United States totaled about $65 million, which is about 8% of the estimated 2017 final product sales of $820 million in the domestic market as estimated by the Hemp Business Journal (2018). USDA AMS (2019) estimates the value of the hemp imports to be about 15% of the raw hemp products’ value. Although the import value share relative to the domestic hemp market is small, it can grow quite large when the U.S. market expands, given the relatively established hemp industry in the exporting countries. The imports from Canada are among the most competitive, as its share in the total U.S. hemp, hemp seed, and hemp oil imports are about 91, 95, and 78 percent, respectively (Table 6).

**Opportunities**

Although the U.S. hemp industry faces many challenges, there have been some positive developments to facilitate the industry’s growth. We discuss below some of those developments and the opportunities created.
Projected growth potential: Although hemp has been grown globally for hundreds of years, its commercial production for CBD and other industrial products has a relatively young history. Therefore, it is a new industry with worldwide growth potential if the benefits of CBD use are scientifically verified in the future. Notwithstanding the pending scientific verification of CBD benefits, optimistic projection suggests that the U.S. CBD market will be $16.8 billion (Brightfield group, 2020) and the hemp producers’ sales to be $1.29 billion (Hemp Industrial Daily, 2021) by 2025. The USDA AMS (2021) projects the number of U.S. hemp grower licenses to increase annually at a 10% rate to 32,210 licenses, planted acres to be about 1.05 million acres, and producers’ sales of $2.86 billion by 2025.

A global industrial hemp market projection claims a compound annual growth rate of 34% and is projected to reach $36 billion by 2026 (Facts and Factors, 2021). Following the World Health Organization recommendation of not scheduling CBD as a controlled substance (Open Access Government, 2020) and the subsequent removal of cannabis for medicinal purposes by the United Nations (Hoban, 2020), many countries in the world are expected to relax regulations on CBD and hemp. These developments are expected to expand the global hemp market and create an opportunity of exporting U.S. hemp.

In light of the market potential, retail giants such as CVS, Walgreens, Kroger, and Albertson have started selling CBD products, and Canadian cannabis companies such as Tilray, Aurora Cannabis, and Canopy Growth have entered the U.S. CBD market (Brightfield group, 2020). Such established companies' entry is expected to bring their expertise and develop the U.S. hemp industry. Consumer awareness of CBD products is also increasing, contributing to a further increase in demand for CBD products (Brightfield group, 2020). There are also opportunities to expand the use of hemp products in textiles, personal care products, automobiles, construction materials, and animal feed. Favorable development of the domestic hemp market can make the United States a dominant player in the world hemp market in the future.

USDA Final Hemp Rule: USDA recently finalized the interim hemp rule (USDA AMS, 2021). The final rule has cemented the legalization of hemp in the United States and provides many concessions to hemp farmers by removing some regulatory constraints they face in producing hemp. The rule expands the "negligent violation" error margin of THC level to 1% from 0.5% and prevents farmers from being criminally charged. Also, farmers can’t be cited for negligent violation more than once in a calendar year even though they get multiple violation citations for hemp grown in different locations in a single season. The rule also provides flexibility to the states and tribal governments in developing THC testing protocols that would not require 100% testing of all hemp lots if they can demonstrate with 95% confidence that hot hemp is not produced. The rule allows hemp farmers to salvage some of their investment by retaining some part of their hemp plant within the statuary THC limit and destroying the part of the plant (e.g., hemp flower) that exceeds the limit. Also, instead of the previous requirement of disposal by government authorized agents, the final rule provides flexibility in destroying hot hemp by the farmers. These policy changes in the final rule would positively impact the growth of the U.S. hemp industry.

As explained previously, the growth potential very much hinges on the growth of the CBD market, which is contingent on scientific verification of claimed health benefits. Given this scenario, cautious optimism should be exercised in reading into the industry growth projections.
**Improved access to credit and financing:** In the past, banks were reluctant to give financial services to hemp-related businesses because of their proximity to marijuana, a controlled substance. Following hemp legalization by the 2018 Farm Bill, the Financial Crimes Enforcement Network, a bureau of the U.S. Department of Treasury, issued guidance to banks that "because hemp is no longer a Schedule I controlled substance under the Controlled Substances Act, banks are not required to file a Suspicious Activity Report (SAR) on customers solely because they are engaged in the growth or cultivation of hemp in accordance with applicable laws and regulations" (FinCEN, 2019). This is a positive development for the hemp industry. The hemp industry is optimistic that the SAFE Banking Act 2021, which was recently passed by the U.S. House of Representatives and is under consideration in the senate, will further facilitate access of hemp businesses to banking services (Smith, 2021). Because access to financial resources is essential for the development of any industry, the policies to facilitate access to financial services contribute to this nascent industry's growth.

**Government support programs:** With the legalization of hemp farming, U.S. hemp producers can access various farm support programs such as crop insurance, farm loan, and farm conservation programs (USDA, 2021). Until 2019, hemp producers operated without any federal crop insurance program designed to cover hemp crops. Hemp farmers can now participate in various government-provided crop insurance programs such as the Multi-Peril Crop Insurance (MPCI), Noninsured Crop Disaster Assistance Program (NAP), Whole-Farm Revenue Protection (WFRP), and Nursery Crop Insurance (NCI), and Nursery Value Select (NVS) programs based on the eligibility criteria for each program (Raszap Skorbianksy, 2021). Although hemp producers are expected to benefit from these insurance programs, crop insurance will not alleviate the risk of hot hemp (hemp with >0.3% THC) since hot hemp is illegal and not covered under the programs.

Unlike other businesses, hemp-related businesses have a hard time securing finances for their business, given that hemp businesses are relatively riskier for investment (Allen and Whitney, 2019). The availability of farm loans through the Farm Service Agency (FSA) would provide an alternative source of financing for hemp producers. The availability of crop insurance programs will also make hemp producers competitive with other businesses to secure loans from private banks as the insurance programs minimize the risk in hemp farming.

**Growth of the legal marijuana industry:** By the end of 2020, there were 37 states that legalized the medical use of marijuana, and 16 states have legalized recreational marijuana (ProCon.org, 2020). There is a bill under consideration in the U.S. Senate to legalize marijuana federally (Lyons, 2021). As more states open legalized marijuana and as long as there is a clear-cut legal separation between hemp and marijuana markets, the hemp industry will benefit from expanding infrastructures such as more processing facilities and new technologies for production and processing. However, it will be exposed to more competition for land, processing facilities, and access to finances from the marijuana industry (Mark et al., 2020).

**The Way Forward**
Based on the previous discussion on challenges and opportunities, in this section, we point out some

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7 It is a pilot program available only in select counties in Alabama, Arizona, Arkansas, California, Colorado, Illinois, Indiana, Kansas, Kentucky, Maine, Michigan, Minnesota, Montana, Nevada, New Mexico, New York, North Carolina, North Dakota, Oklahoma, Oregon, Pennsylvania, Tennessee, Texas, Virginia, and Wisconsin (USDA, 2021).
specific actions that would be helpful for the development of the U.S. hemp industry.

**Growth and development of alternative industrial products:** So far, the entire hemp industry is focused on CBD. Given the optimistic projections and attractive price, many farmers were lured into hemp cultivation for the CBD market, which resulted in an oversupply of hemp and a drastic fall in price in recent years. The enthusiasm was understandable considering the projected growth potential of the industry, but given the drastic fall in price, it is likely that the enthusiasm can quickly dissipate if the supply of hemp is not matched with the increased demand for hemp products. In the absence of adequate demand, the hemp industry can potentially be the next "Emu."

As explained in the previous section, the expansion in CBD demand is contingent on the conclusions of scientific investigation regarding its health benefits and consequent FDA policy on CBD use for medical and food purposes. The FDA might take a long time to issue a policy on hemp-derived products, and there is no guarantee that the policy would favor the hemp industry. Although CBD may continue to dominate the hemp market, the growth of other hemp-derived products for industrial and other uses (e.g., use of hemp oil for producing lubricants, oil paints, varnishes, and personal hygiene products; hemp fiber for textiles, construction, and automobile materials, etc.) is crucial for the survival of this industry. Industrial product growth has been modest. The sales of industrial and other uses of hemp products grew by just 10%, from $403 million in 2016 to $446 million in 2017 (Hemp Business Journal, 2017 and Hemp Business Journal, 2018). Given that FDA has greenlighted the use of hulled hemp seed, hemp seed protein, and hemp seed oil as a food ingredient, hemp has a potential market in the form of plant-based protein. The use of hemp for biofuels and animal feed could be the other possibility. However, it should be noted that the research to develop hemp for biofuels and feed purposes is at its preliminary phase and would require several more years of research to develop these products.

**Scientific investigation on THC threshold policy:** The primary source of risk to hemp producers is the 0.3% THC requirement. The scientific basis of the 0.3% THC rule is not clear. Industry advocates (e.g., Vote Hemp, 2020b) claim that the requirement is "arbitrarily set" by a Canadian scientist, Dr. Ernest Small, in the 1970s and calls it a very stringent criterion for CBD producers. Contrastingly, many European countries have set even higher standards of 0.2% or less THC requirement for CBD products (e.g., France, 0%; Netherlands, 0.05%; Germany, 0.2%, etc.) (Tomares, 2021). It is not clear which one is scientifically determined between the two opposing THC standards. Given this gap, it is a good time for the U.S. government to commission a study to review the scientific basis of the THC level and incorporate that recommendation in the upcoming farm bill.

**Policy segmentation for CBD and non-CBD products:** The current hemp policy does not differentiate hemp producers based on their intended products, i.e., all the regulatory provisions are equally applied to CBD, grain, and fiber producers. Given that the cultivation practices, processing methods, and intended use of CBD, grain, and fiber are drastically different, it would make sense that they are treated as separate industries and regulated under separate policies. That way, the regulatory constraint of one product will not be a bottleneck for the growth and development of other products. For example, CBD is extracted mainly from flower buds and floral materials of hemp plants (Johnson, 2019), whereas grain and fiber are produced from the stalks and seeds of the plant. The THC concentration is relatively higher in flower buds than in the stalks and seeds (USDA AMS, 2021; Johnson, 2019). The likelihood of hemp for non-CBD products (grain and fiber) to exceed
THC requirements compared to CBD is very low (USDA AMS, 2021). Given this fact, it would be arbitrary to impose similar stringent regulations meant for higher THC products on grain and fiber producers primarily using hemp plant parts with less THC concentration.

**Public investment in hemp research:** The lack of proper development of hemp production technology and region-specific varieties are among the most crucial factors constraining hemp farming. Limited market information and analysis inhibit rapid industry growth. Given that hemp research in the United States is in its infancy, the industry would benefit from more research support and development. Developing hemp varieties with wider adaptability, developing new harvesting and post-harvest technologies, and market analysis are the current research needs for the U.S. hemp industry. As the research output comes through, it is expected that many research-related problems on hemp production, processing, and marketing will be resolved.

**Developing a market information system on hemp:** Lack of proper information (e.g., prices, acreage, production, and marketed volume information) is one of the constraints hemp farmers and businesses face when marketing their products. The USDA market report on specialty crops has started publishing hemp seed and oil retail prices, but market information of all hemp products at the farm, wholesale, and retail levels for all regional markets is not available. Such market information is crucial for hemp farmers to get a better price and improve their bottom line. Without readily accessible market information, hemp farmers have to accept the price quoted by the processors, which gives an unfair advantage to the processor in setting the price. Hemp production and market databases will also facilitate accurate production and market analysis and contribute to the development of the industry.

**An online platform for hemp trading:** As discussed previously, there is a lack of established marketing channels or spot markets for U.S. hemp producers. Given the impact of marketing channels on farm profitability (e.g., Lee et al., 2020), the USDA can take the initiative to help producers create the needed infrastructure to facilitate the trading of hemp. For example, a hemp checkoff program could be initiated to fund an online trading platform and other marketing programs. An inventory of U.S. hemp producers and processors could be built into the platform to induce initial trading. Such an online platform would provide hemp buyers and sellers an additional avenue to find each other and develop a competitive hemp market.

**Developing hemp product quality standards:** Currently, there is no standard practice of grading hemp products. Consumers of hemp products are left uninformed about the product’s quality. Having quality standards for hemp products would be beneficial to both consumers and producers, as it would discourage fraudulent practices, and quality products would fetch higher prices in the market. The USDA can take the lead in developing quality standards for hemp.

**Exploring the export potential for U.S. hemp products:** Given that many countries are opening up for hemp, there is a growing international market, which the United States can explore to market domestically produced hemp products. Export to the global market would create additional demand

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8 The USDA has kept hemp as a priority research area in the recent request for proposal for grant funding (USDA-NIFA, 2021a and USDA-NIFA, 2021b).

9 Currently, the FSA reports planted acres for hemp, but it is argued that many of the planted acres were not reported to FSA (Drotleff, 2020). Recently, the USDA NASS announced that they will start surveying hemp farmers to collect the data on hemp production, yield, acreage, and price.
for U.S. hemp and help to mitigate the excess supply of hemp in the domestic market. The USDA Foreign Agricultural Service (FAS) can take the initiative in this regard.

**Concluding Remarks**
The above assessment indicates that although there is considerable enthusiasm for the U.S. hemp industry, there are many challenges that the industry needs to overcome to survive and establish itself. The current situation is fluid, and it is not clear how the industry will evolve in the future. These facts make it a high-risk venture for most producers. It will require a concerted effort and work to mitigate the risk and grow the industry. In this regard, implementing the actions discussed in the previous section are only some of the things that would be helpful. Cautious optimism paired with remembering new products may not blossom into what we might hope or expect would be an appropriate approach.
Table 1: Hemp Production in the United States

<table>
<thead>
<tr>
<th></th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of states licensing hemp</td>
<td>15</td>
<td>19</td>
<td>21</td>
<td>34</td>
<td>47</td>
</tr>
<tr>
<td>Number of hemp licenses issued</td>
<td>817</td>
<td>1,456</td>
<td>3,546</td>
<td>16,877</td>
<td>21,496</td>
</tr>
<tr>
<td>Number of hemp planted acres</td>
<td>9,649</td>
<td>25,713</td>
<td>78,716</td>
<td>230,000</td>
<td>157,082</td>
</tr>
</tbody>
</table>

Source: Vote hemp crop reports based on the data reported by the USDA (Vote Hemp, 2017, 2018, 2019, 2020*) and Drotleff, 2020 (Hemp Industrial Daily). *June 2020 estimate in Drotleff, 2020 includes New Hampshire, which operates under the USDA plan. The data includes hemp acres under state hemp pilot programs approved after the 2014 Farm Bill and state programs after the 2018 Farm Bill.

Table 2: Hemp Planted and Licensed Acres in the Major Hemp Producing States in the United States

<table>
<thead>
<tr>
<th>States</th>
<th>Planted Acres</th>
<th>Licensed Acres</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2019</td>
<td>2020</td>
</tr>
<tr>
<td>Colorado</td>
<td>53,222</td>
<td>20,792</td>
</tr>
<tr>
<td>Kentucky</td>
<td>26,500</td>
<td>5,000</td>
</tr>
<tr>
<td>Montana</td>
<td>45,000</td>
<td>10,950</td>
</tr>
<tr>
<td>Tennessee</td>
<td>*</td>
<td>4,754</td>
</tr>
</tbody>
</table>

Source: Stelton-Holtmeier et al., 2021. * Not available

Table 3: Hemp Seed Budgets ($/acre)

<table>
<thead>
<tr>
<th>Hemp Seed</th>
<th>Mark and Shepherd, 2020 (Kentucky)</th>
<th>Hanchar, 2019 (New York)</th>
<th>Harper et al., 2018 (Pennsylvania)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield (lbs./acre)</td>
<td>1,200</td>
<td>1,000</td>
<td>1,400</td>
</tr>
<tr>
<td>Price ($/lbs.)</td>
<td>0.7</td>
<td>1.11</td>
<td>0.7</td>
</tr>
<tr>
<td>Revenue</td>
<td>840</td>
<td>1,110</td>
<td>980</td>
</tr>
<tr>
<td>Variable cost</td>
<td>735</td>
<td>321</td>
<td>304</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>271</td>
<td>164</td>
<td>129</td>
</tr>
<tr>
<td>Returns above variable cost</td>
<td>-105</td>
<td>789</td>
<td>676</td>
</tr>
<tr>
<td>Returns above the total cost</td>
<td>-166</td>
<td>624</td>
<td>547</td>
</tr>
</tbody>
</table>

Sources: Mark and Shepherd, 2020; Hanchar, 2019; and Harper et al., 2018

Table 4: Hemp Fiber Budgets ($/acre)

<table>
<thead>
<tr>
<th>Hemp Fiber</th>
<th>Mark and Shepherd, 2020 (Kentucky)</th>
<th>Hanchar, 2019 (New York)</th>
<th>Harper et al., 2018 (Pennsylvania)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield (lbs./acre)</td>
<td>10,000</td>
<td>7,940</td>
<td>10,000</td>
</tr>
<tr>
<td>Price ($/lbs.)</td>
<td>0.07</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Revenue</td>
<td>700</td>
<td>794</td>
<td>500</td>
</tr>
<tr>
<td>Variable cost</td>
<td>850</td>
<td>390</td>
<td>280</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>272</td>
<td>156</td>
<td>146</td>
</tr>
<tr>
<td>Returns above variable cost</td>
<td>-150</td>
<td>404</td>
<td>220</td>
</tr>
<tr>
<td>Returns above the total cost</td>
<td>-422</td>
<td>248</td>
<td>74</td>
</tr>
</tbody>
</table>

Sources: Mark and Shepherd, 2020; Hanchar, 2019; and Harper et al., 2018
<table>
<thead>
<tr>
<th></th>
<th>Mark and Shepherd, 2020 (Kentucky)</th>
<th>Cui and Smith, 2020 (Tennessee)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBD % of dry matter</td>
<td>3.5</td>
<td>10</td>
</tr>
<tr>
<td>Price per %</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>Dry matter yield (lbs./acre)</td>
<td>1,500</td>
<td>1,458</td>
</tr>
<tr>
<td>Price ($/lbs.)</td>
<td>3.5</td>
<td>7.5</td>
</tr>
<tr>
<td>Revenue</td>
<td>5,250</td>
<td>10,935</td>
</tr>
<tr>
<td>Variable cost</td>
<td>1,301</td>
<td>11,617</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>606</td>
<td>749</td>
</tr>
<tr>
<td>Returns above variable cost</td>
<td>3,949</td>
<td>-682</td>
</tr>
<tr>
<td>Returns above the total cost</td>
<td>3,343</td>
<td>-1432</td>
</tr>
</tbody>
</table>

Sources: Mark and Shepherd, 2020; and Cui and Smith, 2020
Table 6: A Six-Year Average (2015-2020) of U.S. Import of Hemp Products

<table>
<thead>
<tr>
<th></th>
<th>Canada</th>
<th>China</th>
<th>Europe</th>
<th>World Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw</td>
<td>Proc</td>
<td>Oil</td>
<td>Seed</td>
</tr>
<tr>
<td>Unit Value ($/kg)</td>
<td>3.35</td>
<td>2.53</td>
<td>10.73</td>
<td>9.15</td>
</tr>
<tr>
<td>Qty (tons)</td>
<td>3.9</td>
<td>37.2</td>
<td>677.4</td>
<td>8775.5</td>
</tr>
<tr>
<td>Total Value (FOB $ mil)</td>
<td>0.006</td>
<td>0.064</td>
<td>7.012</td>
<td>52.97</td>
</tr>
</tbody>
</table>

Raw = Raw Hemp, Proc = Processed Hemp
Source: Author’s calculation based on 2015-November 2020 hemp import data for HS5302100000 (raw/processed hemp), HS5302900000 (processed hemp), HS1515908010 (hemp oil), and HS1207990320 (hemp seed) available at USA Trade Online platform of the United States Census Bureau (2021).
*2018 value for raw hemp for China was excluded in the average calculation due to extreme outlier unit values.
References


