Journal of Agricultural and Resource Economics 41(1):97–115 ISSN 1068-5502

Sequential Adoption and Cost Savings from Precision Agriculture

David Schimmelpfennig and Robert Ebel

Precision agricultural (PA) technologies can decrease input costs by providing farmers with more detailed information and application control, but adoption has been sluggish, especially for variable-rate technologies (VRT). Is it possible that farmers have difficulty realizing these cost savings? Combinations of PA technologies are considered as complements, testing several patterns of PA technology adoption that may show different levels of costs. The USDA's Agricultural Resource Management Survey of corn producers is used to estimate a treatment-effects model that allows for selection bias. VRT contributes additional production cost savings when added to soil mapping, but not when done with yield mapping alone.

Key words: crop production information technologies, joint adoption

Introduction

Precision Agriculture (PA) technologies may be used to improve farm management by providing timely, detailed, site-specific farm production information. A central concern is whether input costs can be saved by providing the farm operator with detailed production information (Tozer, 2009). In spite of theoretically possible cost-savings from the use of global positioning system (GPS) soil mapping, yield mapping (Ymap), equipment auto-guidance systems (GSYS), and variable-rate input application (VRT), adoption has been far from universal, even in U.S. cereal and grain crop production, where they are the most popular. Bramley (2009) discussed possible factors explaining slow PA adoption of individual technologies even with apparent cost savings.

One possible explanation for sluggish adoption is that the technologies may be worked into production practices sequentially. The one-technology-at-a-time approach to adoption may seem inefficient and time-consuming compared to adoption of complete, possibly complementary, packages of technologies, but this scheme has been shown to occur in other settings. Soil testing and VRT were tested as a sequential pair by Isik, Khanna, and Winter-Nelson (2001) in an option-value framework like Tozer's 2009. Tozer highlighted irreversibility and uncertainty in the cost of PA adoption, and these costs could be counted against any potential cost savings. Isik, Khanna, and Winter-Nelson considered the impact of output price uncertainty, high sunk costs of technology investment, and farm-site specific factors on how value is created from having the option to use the information technologies either sequentially or jointly. More recently, Aldana et al. (2011) implemented a Bayesian updating model to explain how farmer uncertainty concerning crop technology packages that included single- and stacked-trait corn varieties led to a sequential

David Schimmelpfennig is a senior economist at the Economic Research Service and Robert Ebel is a risk management specialist with the Risk Management Agency, both at the U.S. Department of Agriculture.
The authors would like to thank two insightful referees, Jim MacDonald for tireless support for the analysis of precision agriculture using ARMS data, and Ryan Williams (ERS-USDA) for useful discussions and developing farm-specific data for this project. The views expressed are those of the authors and should not be attributed to the Economic Research Service or the U.S. Department of Agriculture.
Review coordinated by Larry Makus.

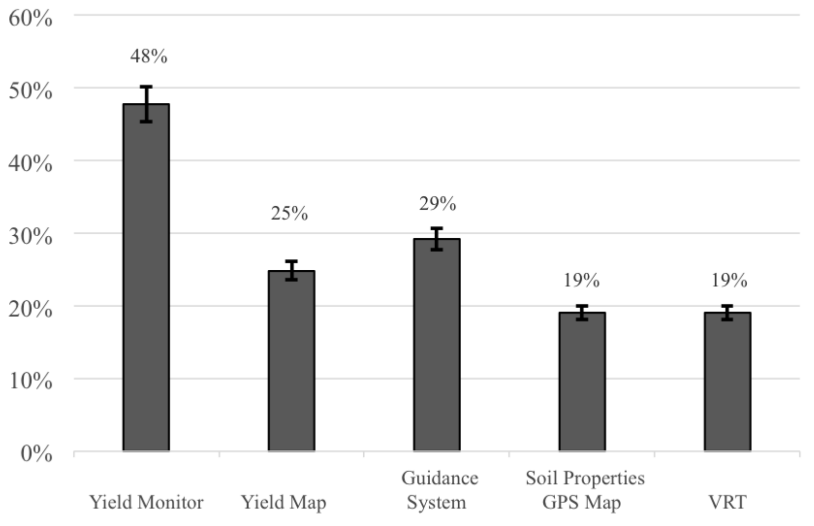

Figure 1. Adoption of PA Technologies among Corn Farms

Notes: Error bars represent positive and negative standard errors of the mean percent estimates.
Source: 2010 USDA Agricultural Resource Management Survey (ARMS).

adoption pattern. They found that success with individual-trait corn varieties and farmer education influenced further adoption.

Byerlee and de Polanco (1986) found similar results in Mexico with packages of technologies that were shown to work well together and were promoted as complementary packages by extension agents. Even though the experts said the technologies went together, farmers were inclined to subdivide and adopt them sequentially. Their research found that profitability and risks associated with individual elements of technology packages influenced the adoption rate of each element. Leathers and Smale (1991) made the process more explicit in a Bayesian learning model, finding that sequentially testing out elements of a new package of technologies on the farm was rational even under assumptions of risk neutrality and unconstrained expenditures because of the "possible" resolution of uncertainty concerning farm-specific impacts. Farmers were found to adopt technologies sequentially to learn about the sub-components, even when the package is more profitable as a whole. Both of these studies found that sequential adoption takes place even though there are complementarities between elements of the technological package.

Our analysis contributes to this literature by considering the sequential paths of PA technology adoption that U.S. corn farmers have taken and whether other farm-level production practices, like no-till, influence cost savings when different elements of PA are adopted together. The main question addressed is whether farm-level cost data may indicate a cost hierarchy of adoption when heterogeneous farm-level factors are taken into account. Bullock et al. (2009) discussed how complementary information collected from different PA technologies can theoretically create more production value than the sum of individual information technologies alone. Figure 1 shows that yield monitoring (YM) was adopted by over 40% of U.S. corn producers in 2010, but this technology merely represents a data collection stage in PA implementation and many new combines have them as standard equipment. The second most popular technology was GSYS, with 29% adoption by U.S. corn farmers.

The mix of PA technologies used in U.S. corn production has been changing rapidly, with a 2005 survey of corn producers showing only 15% adoption of GSYS and 12% adoption of VRT (19% by 2010), while YM showed a small increase from 2005 to the 2010 value shown in figure 1 (42% to 48%) and GPS soil properties mapping increased from 15% to 19% adoption (Schimmelpfennig and Ebel, 2011). The error bars on figure 1 show significant differences between mean estimates for YM, yield mapping, and guidance in 2010. This paper estimates aggregate impacts of sequential PA technology adoption in U.S. corn production using farmer-reported individual farm costs. YM is treated as the first-step technology because it is the most popular and to establish a base-cost case before YM is added to other possibly complementary PA technologies. This approach allows evaluation of cost savings from the most popular information technologies and of whether there are cost-savings synergies involved when PA technologies such as GPS and Ymap are adopted with YM. VRT is then added to the cost scenarios.[1]

Most of the PA combinations investigated show some cost savings, but only one of the three combinations that added VRT showed extra cost savings. VRT added savings to GPS soil mapping and YM. The highest cost savings for any individual combination of PA technologies was for YM and Ymap.[2] Comparing results for different combinations of technologies, it is also possible to discern the characteristics of producers who adopt them, These are shown with each of the scenarios. As the demand for high-efficiency production continues to surge, particularly in large-scale agricultural settings, what explains the patterns of PA adoption? We investigate whether this question can be answered from collected farm production data.

ARMS Data

The data to test patterns of PA adoption come from the USDA's Agricultural Resource Management Survey (ARMS), which is jointly administered by the USDA's National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) and collects data on field-level production practices and farm finances. The ARMS organizes highly detailed data from individual farms on resources required for agricultural production (Phase II), including seeds, fertilizer, pesticides, machinery, labor, and the use of information technologies as well as yield data obtained in its first questionnaire. Phase I identifies the sample of farms that will be used to create nationally representative data. A follow-up questionnaire (Phase III) collects expenditures on fixed inputs like machinery as well as farm operator characteristics such as educational attainment, age, and off-farm income.

The ARMS is conducted annually on several different commodity crops so that data are obtained on most major crops over several years. Descriptive PA data for other years and crops can be found in Schimmelpfennig and Ebel (2011). The 2010 corn survey was an auspicious year for ARMS data in that most farms completed both questionnaires, creating a dataset with 1,507 observations on all the variables. The 2010 corn survey provides a comprehensive dataset with information on each respondent's use of precision technologies, costs of production, and demographic profile. Copies of the survey questionnaires, additional details about the data, and some tailored reports can be found at http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation.aspx#about.

Descriptive statistics for selected variables used in the empirical models are presented in table 1. The top section shows indicator variables for adoption of combinations of PA technologies, so mean values are full-sample adoption rates for combinations of technologies. Each specific combination of PA technologies is coded 1 for "yes" if both technologies are used together (not coded 1 if only one technology is used) and 0 otherwise. As can be seen on the table, when VRT is added to any of the other combinations of technologies, the adoption rate for all three PA technologies drops to 8–9%. This fact ruled out consideration of the full suite of three or four other technologies with VRT because the adoption percentages became too small for reliable results.

[1] We constructed several scenarios that had four PA technologies in use together, but none of them had sufficient observations to reliably estimate the model.

[2] Cost savings, as the term is used, refer to differences in variable production costs between production systems that include the PA technologies and those that do not. Some of the actual savings may be attributable to differences in practices not specifically linked to the PA technologies, but these secondary sources of savings are hard to isolate separately.

Table 1. Descriptive Statistics for PA Technology Combinations and Variables used in Empirical Models

Technologies/Variables	Mean	Min.	Max.	St. Dev.
Yield monitoring (YM)[a]	0.43	0	1	0.54
YM + yield mapping (Ymap)[a]	0.22	0	1	0.34
YM + Ymap + VRT[a]	0.09	0	1	0.13
YM + soil mapping (Soil)[a]	0.14	0	1	0.27
YM + Soil + VRT[a]	0.08	0	1	0.14
YM + guidance system (GSYS)[a]	0.20	0	1	0.36
YM + GSYS + VRT[a]	0.08	0	1	0.11
Higher education (college)[a]	0.50	0	1	0.50
Soil testing[a]	0.32	0	1	0.47
Off-farm income[a]	0.29	0	1	0.46
GMO seed use[a]	0.92	0	1	0.27
No-till[a]	0.25	0	1	0.43
Irrigated[a]	0.10	0	1	0.30
Operator age	54.74	22	97	13.84
Acres farmed	409.61	0.3	10,235	667.00
Variable production cost (per acre)	$265.66	$49.95	$751.44	$381.67
Yield goal (bushels per acre)	157.68	30	300	39.13

Notes: Superscript [a] indicates dummy variables equal to 1 if yes, 0 otherwise.
Source: USDA Agricultural Resource Management Survey (ARMS)

Corn enterprise acreage (farm size), operator age, variable production cost (per acre), and yield goal are continuous non-negative variables. Larger farms may be more likely to adopt information technologies with more acres to apply the associated start-up costs. Several operators in the dataset are in their nineties and must therefore be making use of farm managers. Older owner-operators may be less inclined to agree to pay for new information technologies when previous practices worked well enough. This may show up as a negative sign in relation to technology selection. Per acre variable production cost is measured as operating costs for seed, fertilizer, pesticides, paid and unpaid labor, machinery service flows (not capital investments), fuel and repairs, and custom service expenses. Variable cost enters as a dependent variable.

The survey question for yield goal simply asks for the yield goal in bushels of corn at planting. Yield goal gives an indication of the producer's perception of expected productivity that they are assumed to use in managing their operation. The minimum yield goal is only 30 bushels per acre and farmers have been taken out of the sample if they indicated that they were only growing corn for silage. Yield goals are probably carefully considered as they must relate to land cash rental rates, so we expect this variable to be more grounded in experience than merely opinion or wishful thinking. Higher yield goals might be expected to positively influence costs as additional expenses are incurred to raise yields.

The rest of the variables are dummy variables coded with 1 for yes and 0 otherwise. Higher education is coded yes for one or more years completed in college. Respondents are asked to answer yes if they completed one or more years toward either an associate or undergraduate degree and might be expected to have had more exposure to computer-based technologies. Soil testing is a separate variable than soil tests commonly associated with mapping. These are full-nutrient diagnostic tests that include micro-nutrients often carried out on one or at most a few sites per farm, whereas soil mapping refers to higher-frequency grid-sampled soil tests on a few nutrients at most. The sensors available for these tests are evolving rapidly, but in 2010 full-nutrient soil tests were sent off-site and it took several days to get results, whereas soil maps were usually generated using on-farm technologies. These two types of testing could be complements with detailed soil tests possibly positively associated with soil mapping and other PA technologies.

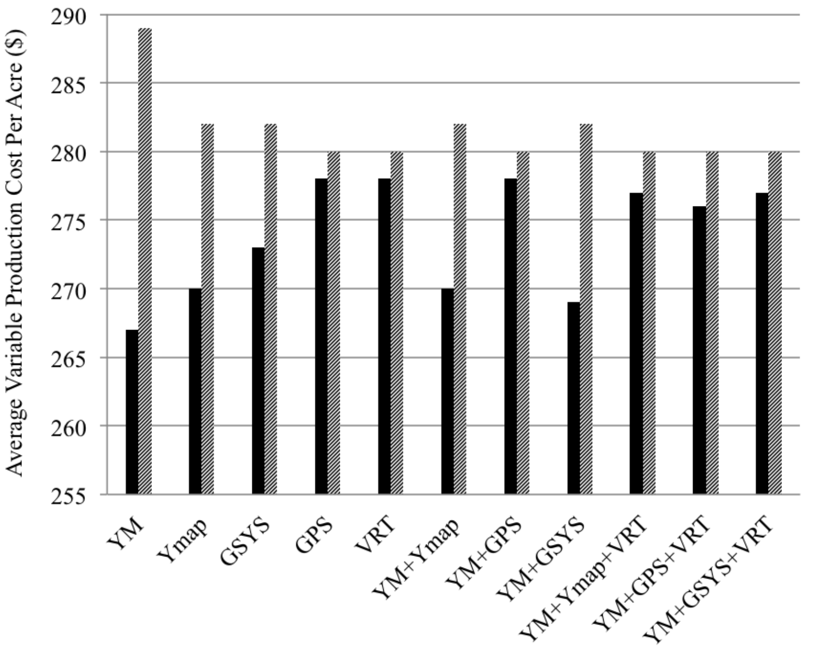

Figure 2. Production Costs[a] with (in black) and without (striped) PA Technologies

Notes: Numbers of farmers in each group are shown in figures 3, 4, and 5 with adoption percentages.
[a]Differences in per acre costs statistically different at 99% confidence level, except for GPS, VRT, and YM+GPS.
Source: 2010 USDA Agricultural Resource Management Survey.

Off-farm income is reported for the farm-family and might be expected to increase capital available to the farm to adopt information technologies. The reverse could also be true: off-farm income might subtract from time available to consider and adopt PA technologies. GMO seed use refers to any genetically engineered seed variety and might be positively associated with adoption as another new technology. No-till refers to the definition used by the Natural Resource Conservation Service (NRCS) that is separate from mulch till, ridge till, and strip till, which are also conservation tillage practices.[3] Production costs might be expected to be lower with no-till as this method requires fewer field operations, but they might also come with increased management requirements compared to conventional tillage, which is often used to address several concerns in one field operation. Irrigation refers to all irrigation practices, which are often associated with more intensive corn management and higher costs. Regional dummy variables include the following states (sample size): Appalachian ($n = 79$) (Kentucky, Pennsylvania), Corn Belt ($n = 522$) (Illinois, Indiana, Iowa, Ohio, Missouri), Delta ($n = 89$) (Arkansas, Mississippi), Lake States ($n = 192$) (Michigan, Minnesota, Wisconsin), Mountain ($n = 104$) (Colorado, Texas), Northeast ($n = 65$) (Connecticut, New York), Northern ($n = 299$) (Kansas, Nebraska, North Dakota, South Dakota), and Southeast ($n = 104$) (Georgia, North Carolina).

Figure 2 shows average variable production costs per acre for corn producers who use individual precision technologies or groups of technologies. This is the cost variable used in the analysis.[4] The figure shows that compared to all other producers that do not use precision technologies, the PA technology users have lower average variable costs. The technology categories on the horizontal axis represent yes/no answers to survey questions concerning the use of each technology (i.e., YM or VRT). The combinations of technologies (for example YM+Ymap or YM+Ymap+VRT) show

---

[3] Definitions and discussion are available at: https://www.extension.purdue.edu/extmedia/ct/ct-1.html.

[4] Production costs per unit of land rather than costs per unit of output or per value of output are used because we want to standardize on the most variable factor between farms—farm size.

yes/no answers for two or three technologies used together by the same farmer. It may not be surprising that farmers that take the effort to manage with information technologies have lower input costs, but these could also be larger farms and additional empirical modeling is necessary to isolate confounding effects like these.

Model Specification

Figure 1 presents evidence that PA technologies have been adopted on less than half of U.S. corn farms, but average variable production costs (shown in figure 2) are lower for adopters of the individual technologies. When two or even three of the technologies have been adopted together the lower cost pattern persists in figure 2. To examine the empirical relationship between average variable costs and the technologies, three adoption scenarios consistent with the adoption percentages are envisioned. All three scenarios start with YM adoption, as this is the most widely used technology in the dataset and provides, possibly coincidentally, the most detailed georeferenced data. Discussions with farmers and industry representatives seem to indicate that YM popularity is most closely related to ease-of-use, a trait partially shared with GSYS, which reduces the time that operators must control equipment steering. Little technical computer know-how is required to take advantage of these technologies, as both are practically "plug-and-play."

YM is then considered with three possible additional technologies: yield mapping (Ymap), Global Positioning System (GPS) soil properties mapping, and machinery auto-guidance systems (GSYS). Ymap or GPS could have been treated as the base technologies in place of YM, but a hierarchy of adoption should start with a fairly widely adopted element to get the clearest possible picture of the cost impacts when adopters get weeded out when a new element is added. VRT adoption is added to all the combinations of YM and the additional technologies at the end. VRT represents the downstream production practice technology that relies on information collected using the other technologies. This selection process yields three reasonable scenarios of adoption based on the actual use of the technologies for corn production in 2010.

For each of these scenarios, a treatment-effects model is developed to estimate the impact of the PA technologies on corn production costs. The treatment-effects approach is used because the impact of PA technologies on costs may be confounded with factors explaining their adoption (Imbens and Wooldridge, 2009). The treatment-effects model has an advantage for this application over other selection-bias models because it allows us to use observations on explanatory variables for both adopting and non-adopting producers and to include the endogenous dummy variable for technology selection in one estimation procedure.[5] The final results using the treatment-effects model show significant factors influencing adoption and a separate set of factors explaining costs; both sections of the model include the PA technology. In the first selection section, the technology is a binary dependent variable, estimated in a standard Probit model. In the second cost section, the fitted values from the selection equation are used as an explanatory variable representing the PA technology in explaining costs.

This empirical approach creates a robust model that differentiates factors explaining technology adoption from those that might also explain costs. The model is robust because it corrects for bias that can be caused by self-selection (technology adopters may have had lower costs regardless of the technology) and simultaneity (adoption and cost may be determined by similar variables) as discussed by Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) for other farm technologies. The variables in the adoption section and those in the cost section are determined by evaluating model fit (Akaike Information Criteria statistics are reported with the tables of results) and parameter parsimony. All continuous variables have been converted to logarithms.

A final step in model specification involves testing that the adoption equation is not independent of the equation explaining costs. If these two estimated components of the model were found to be independent of each other, it would indicate that costs were not being influenced by the decision

[5] http://www.stata.com/stata13/treatment-effects/

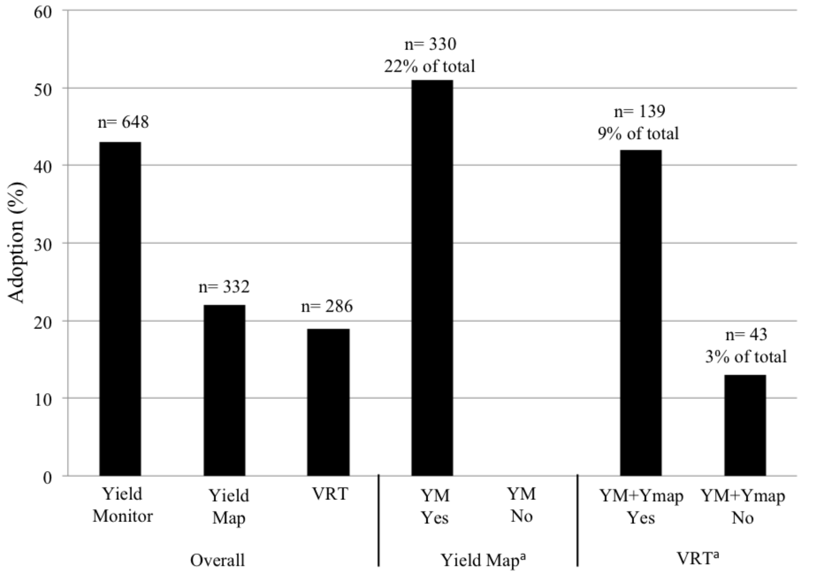

Figure 3. Scenario 1: Joint Adoption of PA Technologies among Corn Farms (Yield Map if Yield Monitor, VRT if YM and Ymap, $n = 1,507$)

Notes: YM = Yield Monitor; Ymap = Yield Map; VRT = Variable Rate Technology. [a]Adoption percentages statistically different at 99% confidence level.
Source: 2010 USDA Agricultural Resource Management Survey (ARMS).

to adopt. If this were the case, the two sections of the model could be estimated and interpreted independently. The test statistic for this comes from the Wald test reported near the top of each set of treatment-effects results and gives the selection-corrected impact of the PA technology on costs, controlling for the other variables explaining cost in the "corrected equation."

Adoption Scenario 1: Monitor to Map to VRT

The first scenario considered is one in which the yield data produced by the most popular PA technology (YM) might be collected and analyzed in the form of a yield map of a farmer's corn field. Yield mapping was chosen for the first scenario because mapping capability could not have been ruled out by farmers because of a lack of appropriate data—the farmers in these models had already adopted the yield-monitoring technology that collects the necessary data with GPS coordinates attached. Yield maps can help indicate areas where farmers are obtaining reduced yields and where less fertilizer might be applied or planting density decreased to reduce costs. Focusing only on avoiding wasted inputs to reduce costs helps avoid aggregation bias associated with optimizing inputs for yield/output and crop price tradeoffs that might be handled differently by different farmers. Producers often do not maximize output when input prices are too high for expected crop prices.

YM adoption is nearly twice as prevalent as either yield mapping or VRT (figure 3). The "yield map" columns show that producers must have adopted YM in order to create a yield map because the monitor produces the data necessary to make a yield map. About half of the farmers with YM created yield maps (22% of all surveyed farmers). Farmers responding to the ARMS also answered individual questions about whether they used their yield data to monitor crop moisture for drying, need for drainage tile, irrigation equipment setup, in-field experiments, negotiating crop leases, crop insurance documentation, or share cropping. Yield maps are often created on a personal computer using appropriate software, but there are several mobile computers available that can be used to organize and present geolocated yield data from the cabs of farm machinery and can subsequently be used to control electronic connections to VRT application equipment. For those producers who take the steps to collect yield data and organize the data as a computer map, over 40% also make use of VRT; this is about 9% of all surveyed farmers.[6]

Griffin et al. (2008) conducted a three-year study of yield monitor use and found similar low levels of yield mapping, but split-field management and other integration of yield data in decision making among adopters indicated several avenues for possible cost savings. Pringle et al. (2003) formulated an Opportunity Index for exploitation of Australian yield maps over time, a technique that could possibly be used in other countries. Roberts et al. (2006) illustrated the possible intricacies in successful implementation of VRT in cotton production. Significant McNemar test results (applicable to marginal frequencies of two binary outcomes Stata, 2013) for differences in these mean adoption percentages in figure 3 argue for sequential adoption of yield monitoring, yield mapping, and VRT technologies. Since the "yes" columns are significantly different and higher than the "no" columns in figure 3 the evidence points to the "yes" technologies as predecessors. The separate variables explaining adoption and impacts on average variable costs are discussed in the next section to address whether U.S. corn producers in aggregate experience cost savings from these technologies.

Scenario 1 Results: Monitor to Map to VRT

To present the results for this first scenario, three sets of technology adoption estimates are shown in table 2. The first column shows the results just for YM adoption. The next column has the results for farmers who adopted both YM and Ymap. The final column shows YM, Ymap, and VRT farmers. The top (selection equation) section shows estimates of the impact of the selection variables on the adoption of each of the three sets of technologies to compare estimated adoption results from one step to the next in the sequential adoption process. The corrected regression section in the lower portion of the table, shows average variable producer cost impacts of the cost variables when controlling for the adoption decision.

The three sets of results for this technology adoption scenario are logically consistent and robust across the three nested adoption equations. In the selection equation, acres (farm size), farmer education, soil test, and genetically modified seed use (GMO) showing adoption of another crop-production technology are positive and statistically significant in all three equations, indicating that all four variables increase adoption. The coefficients on education increase with the number of PA technologies considered, indicating a possibly greater value of education as technological sophistication increases. Larger farms have a smaller coefficient with increased technology, but the effect is small, perhaps indicating some muted economies of size. Off-farm income is not significant, appearing to indicate that the availability of alternate sources of income does not increase the selection of these technologies, which is also true for operator age.

While these results for the adoption of yield mapping with YM are unsurprising, the stability and robustness of the estimated coefficients when VRT is also included provides deeper insights. VRT alone has only a 19% adoption rate, but re-examining figure 3 shows that the adoption rate is over 40% among producers who also used YM and created yield maps, about the same as for YM on its own. This indicates that producers who have YM and create maps are about as likely to use them for VRT as farmers starting out with YM. The Wald treatment-effects test is highly significant in all three of the nested models, which indicates that the models are correctly specified; the selection effects for adoption of the technologies do need to be included in the corrected (OLS) regression, and those results can be reliably interpreted.

The Wald treatment-effects can be interpreted as the per acre cost difference between PA-adopting farms and non-adopting farms. Since the fitted values from table 1 are used to estimate

[6] It might seem that the number of farmers in the center "yield map" section of figure 3 that chose to yield map ($n = 330$) should be split into either VRT adopters ($n = 139$) or VRT non-adopters ($n = 43$) in the far right columns. But there are missing observations; surveyed farmers are given the option to refuse to answer a question or to have it recorded that they don't know. The sum on the right cannot exceed the center column. This is also true in figures 4 and 5.

Table 2. Treatment-Effects Model—Maximum Likelihood Estimates for Yield Mapping ($n = 1,507$)

Variables		Entry Adoption (Yield Monitor/YM)	Intermediate Adoption (YM + Yield Map/Ymap)	Advanced Adoption (YM + YMap + VRT)
Wald Treatment Test	Technology adoption cost effect	−14.50**	−25.01***	−21.87***
		(5.94)	(5.95)	(6.97)
Akaike Information Criterion (AIC)/N		12.91	12.47	12.12
Selection (Probit) Equation	Yield Monitor, Yield Map, VRT[a]			
	Acres farmed	0.00012***	0.000073***	0.000066***
		(0.000013)	(0.000013)	(0.000020)
	Higher education[a]	0.22***	0.27***	0.35***
		(0.06)	(0.06)	(0.09)
	Soil testing[a]	0.21***	0.18***	0.23***
		(0.06)	(0.06)	(0.09)
	Off-farm income[a]	−0.033	−0.015	0.079
		(0.16)	(0.07)	(0.09)
	Operator age	−0.0027	−0.0027	−0.0029
		(0.16)	(0.002)	(0.003)
	GMO seed use[a]	0.31***	0.38***	0.38***
		(0.09)	(0.11)	(0.14)
	Constant	−0.81***	−1.46***	−2.01***
		(0.16)	(0.18)	(0.25)
Corrected (OLS) Equation	Variable production cost (per acre)			
	No-till[a]	−12.99***	−11.44**	−13.16**
		(5.55)	(5.30)	(5.61)
	Irrigated[a]	39.57***	38.63***	39.91***
		(8.78)	(8.95)	(9.16)
	Yield goal	0.59***	0.60***	0.56***
		(0.06)	(0.06)	(0.06)
	Mountain[a]	−28.55	−18.10	−24.19
		(17.38)	(15.83)	(20.74)
	Southeast[a]	88.53***	86.15***	89.91***
		(13.78)	(13.49)	(13.85)
	Corn Belt[a]	44.68***	42.11***	42.82***
		(11.23)	(11.71)	(12.41)
	Northern[a]	−24.23***	−24.80***	−21.68***
		(11.04)	(11.35)	(12.07)
	Appalachian[a]	46.42***	41.48***	42.88***
		(13.04)	(13.13)	(14.00)
	Lake States[a]	63.76***	56.04***	58.59***
		(11.64)	(12.11)	(12.50)
	Northeast[a]	141.01***	135.66***	138.42***
		(12.24)	(12.59)	(12.92)
	Constant	88.77***	112.31***	130.41***
		(14.18)	(13.69)	(14.05)

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Standard errors are in parentheses. Superscript[a] indicates dummy variables equal to 1 if yes, 0 otherwise.
Source: ERS analysis of USDA Agricultural Resource Management Survey (ARMS) data.

this coefficient, the mean of those fitted values (one by construction) is multiplied by the coefficient to determine the impact of the technologies on costs. The units on this estimated effect are the units from the dependent variable (variable cost per acre). For scenario 1, estimated YM savings are only −$14.50/acre, and the largest average variable cost savings is seen for the "intermediate" combination of YM and yield mapping. This individual combination of PA technologies has the highest cost savings (−$25.01/acre) of any of those tested in any of the scenarios. When adding VRT to the combination of YM and yield mapping, the increase in the Wald test statistic (−$21.87/acre) indicates less savings and suggests that, on average, VRT does not further enhance cost savings (Wald does not become more negative). This result is consistent with observed lower adoption rates for VRT—some farmers find additional cost savings with VRT but, on average, monitoring and mapping provide the majority of insights on potential production cost savings. Rather than being a waste of resources if VRT is not implemented, the collection and mapping of information alone can be used to save costs in U.S. corn production. Capital costs are not included, but VRT is a capital-intensive step that would also require learning to program the VRT controllers using mapped data; these may both contribute to the lower rates of adoption.

The corrected equation results indicate that after controlling for corn farmers that selected these "scenario 1" technologies, yield goal and irrigation were both positive and significant, which is as expected since these variables measure production expectations that could increase costs and production intensity. Yield goal is a survey question designed to capture a farmer's perceived yield potential on a field and is probably most closely related to land quality. At mean values, a 1% increase in yield goal (which is over 1.5 bushels per acre) increases variable costs by about 35% across the entire sample when controlling for the fact that some farmers are adopters of the PA technologies. This gives an indication that corn producers are applying inputs close to the yield potential for their land because raising yield goal adds substantially to costs even when PA technologies could be in use.

No-till is negative and significant across technologies, indicating that the use of no-till is associated with lower variable production costs on average for all corn farmers after controlling for differences in production practices associated with scenario 1 PA adopters. Use of no-till has been increasing (Horowitz, Ebel, and Ueda, 2010), possibly partly due to cost savings, as it reduces numbers of passes over fields, lowering machinery and fuel costs. The estimated savings in average variable costs from no-till after controlling for use of any of the three sets of PA technologies in table 2 is about 1.2%, or $3.20 per acre.

Factors similar to ours were considered in studies of the adoption of no-till practices, indicating possibly that these adoption variables are correct. Davey and Furtan (2008) include operation acreage, operator age, education, and off-farm income. D'Emden, Llewellyn, and Burton (2008) test farm size, education, and extension variables probably most closely related to our soil test. A broader survey of PA adoption (Tey and Brindal, 2012) found that all the same variables as ours, except GMO seeds, impacted PA adoption.

Regional dummy variables are all significant except for the Mountain region, reflecting regional differences in cost impacts of application of these precision technologies. The Delta region is omitted (no observations from the Southern Plains or Pacific regions were captured in the survey), so regional differences in corn production costs can be interpreted relative to the Delta. The regional dummies have similar sizes across technology adoption nested models but are understandably quite different across regions with wide differences in production practices, particularly in the use of no-till and irrigation for corn. The Northern and Mountain regions show significantly lower average variable costs relative to the Delta region after controlling for scenario 1 PA adoption.

Adoption Scenario 2: Monitor to Mapped Soil Testing to VRT

The second scenario considered is one in which the data produced by the most popular PA technology (YM) might be combined with GPS-based mapping of farm soil properties (GPS).

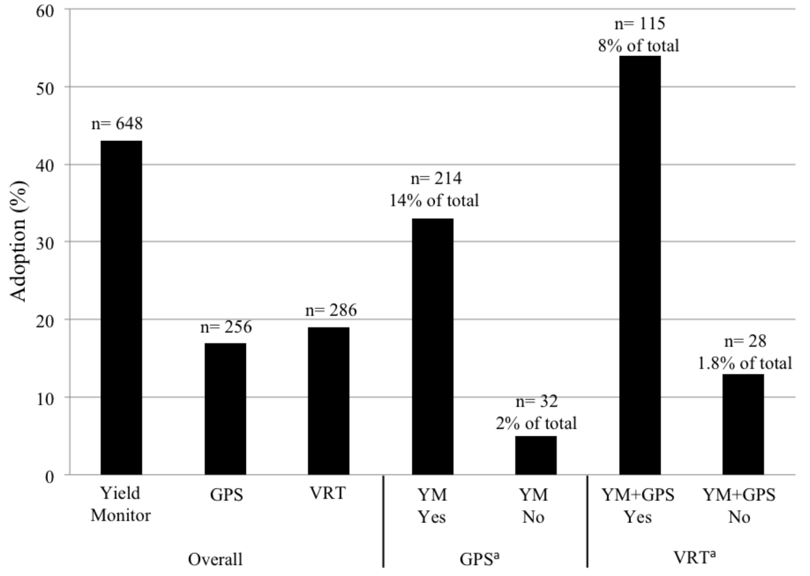

Figure 4. Scenario 2: Joint Adoption of PA Technologies among Corn Farms (Soil GPS if Yield Monitor, VRT if Yield Monitor and Soil GPS, $n = 1,507$)

Notes: YM = Yield Monitor; GPS = GPS Soil Properties Map; VRT = Variable Rate Technology.
[a]Adoption percentages statistically different at 99% confidence level.
Source: 2010 USDA Agricultural Resource Management Survey (ARMS).

Soil mapping was chosen for this second scenario because of the impression that this element of PA is often a precursor to VRT since nitrogen, phosphorus, and potassium can all be applied at different variable rates. Magri et al. (2005) specifically link soil testing and yield data to corn site-specific management. Lambert et al. (2014) use similar variables (farm size, farming experience, and electrical conductivity soil testing) to examine precision soil testing in cotton production. Compared to yield mapping, the data for soil maps is difficult and time consuming to collect. YM data is often first used to create the georeferenced outline of a farmer's field. Soil properties data—including nitrate levels, acidity, and type of soil—are often mapped within those boundaries. Farmers were asked whether soil tests from core samples or electrical conductivity tests were used to collect this information. VRT can save costs by applying nutrients where needed; VRT may not even be implemented if the map indicates that nutrient levels and variability are insufficient to warrant its use. Costs could also be saved if nutrients were being uniformly over-applied, as has often been the case for nitrogen.

Figure 4 shows that YM adoption is over twice as prevalent as either GPS or VRT. Additionally, producers who have adopted YM are far more likely to have also used GPS to create a soil nutrient map than those that had not adopted YM. This represents 14% of all surveyed farmers, whereas only 2% of all farmers generated GPS maps without YM. Maps like these can also be created using electromagnetic soil surveys that monitor soil salinity and locate areas of nutrient build-up in soils. Many producers take advantage of input providers and co-ops for analysis and mapping of yield and soils data and these are included as farmer adoption of the technology.

Soil nutrient maps, often paired with elevation-change or topographic information, can be used to program electronic application rate controllers on VRT equipment. For those producers who make the effort to collect and map soils data, over 50% also make use of VRT (8% of the total surveyed; see figure 4). The effort required to create soil maps may require a greater commitment to VRT than yield mapping. Fountas et al. (2005) find soil maps to be more valuable than yield maps for saving costs for corn PA applications in Denmark and the Eastern Corn Belt, but the point seems open to debate, as Miao, Mulla, and Robert (2006) use both types of maps to manage within-field variability and costs for variable corn seeding.

Magri et al. (2005) use both map types for corn production together with aerial imagery. Fleming et al. (2000) use both map types in a center-pivot irrigation system, arguing that aerial photographs can complement soil and yield maps. These articles seem to indicate possible cost savings from soil mapping even when more readily available yield data have been mapped. Significant McNemar results for differences in mean adoption percentages in figure 4 argue for sequential adoption of yield monitoring, GPS soil mapping, and VRT technologies since the "yes" columns are significantly different and higher than the "no" columns. Supporting this sequential scenario and signaling the need to consider cost impacts of mapping with and without VRT, Robertson et al. (2012) report that a significant number of Australian grain growers use soil tests and manually operated variable-rate systems without creating yield maps.

Scenario 2 Results: Monitor to Mapped Soil Testing to VRT

Table 3 presents three sets of estimates of the impact of the selection variables on the sequential steps in technology adoption. The results for YM adoption are the same as for scenario 1 and are shown again for comparison. As before, the treatment-effects model allows estimation of the impacts of yield goals set by the farmer, irrigation use, and no-till on farm production costs when the adoption of these PA technologies has been taken into account. The same sets of variables are used in each of the sequential adoption models and are the same as for the previous scenario.

In the selection sections, acres (farm size), farmer education, soil test (not necessarily geolocated for mapping), and genetically modified seed use are positive and significant as in table 3 (except for GMO use, which is not significant in the VRT equation). The coefficients on education increase, as in scenario 1, indicating a possible contribution of education to adoption as technological sophistication of PA increases. Farm size again has a larger coefficient with increased technology. Off-farm income is only significant in the VRT equation and operator age is not significant in either equation, indicating that these factors do not increase the selection of these technologies very much.

A joint test of the selection variables for each technology adoption sequence in scenario 2 is given by the Wald treatment-effects test, which is highly significant in both new models. This indicates that the treatments capture the selection effects and the corrected (OLS) regression results can be reliably interpreted. The result of the Wald is that precision technology adoption has a negative relationship with production cost. This scenario is the only one of three considered in this paper for which cost savings increase from intermediate (−\$13.45/acre) to advanced (−\$20.56/acre). This may indicate that, in aggregate for corn production, VRT needs to be implemented with a GPS-based soil properties map to obtain the highest production cost savings through a more optimal use of inputs and precise applications across a field. Alternatively, the previous scenario that included yield mapping in place of soil mapping could be showing the potential to apply more fertilizer at higher cost but perhaps also higher profit.[7]

When the impact of these scenario 2 PA technologies is taken into account, yield goal and irrigation are both positive and significant for all farmers in the corrected regression, as in scenario 1, indicating higher associated costs. Again, no-till is negative and significant across technologies, indicating that (as in scenario 1) the use of no-till is associated with lower costs when PA technologies are taken into account. No-till reduces numbers of passes over fields, lowering machinery costs, more than off-setting the higher required pesticide costs usually associated with no-till. The estimated savings in average variable costs from no-till for all farmers after controlling for use of any of the three sets of PA technologies in table 3 is about 1%, or \$2.80 per acre. The increase in aggregate variable costs associated with an increase in yield goal, after accounting for the PA technologies, is about the same as in scenario 1.

[7] Impacts of PA technologies on profit rather than costs will be considered in future work.

Table 3. Treatment-Effects Model—Maximum Likelihood Estimates for GPS Soil Mapping ($n = 1,507$)

Variables		**Entry Adoption (Yield Monitor/YM)**	**Intermediate Adoption (YM + GPS Soil Mapping)**	**Advanced Adoption (YM + Soil Map + VRT)**
Wald Treatment Test	Technology adoption cost effect	−14.50**	−13.45***	−20.56***
		(5.94)	(6.32)	(7.34)
Akaike Information Criterion (AIC)/N		12.91	12.28	12.07
Selection (Probit) Equation	Yield Monitor, Yield Map, VRT[a]			
	Acres farmed	0.00012***	0.000054***	0.000061***
		(0.000013)	(0.000016)	(0.000021)
	Higher education[a]	0.22***	0.22***	0.35***
		(0.06)	(0.07)	(0.11)
	Soil testing[a]	0.21***	0.31***	0.37***
		(0.06)	(0.07)	(0.09)
	Off-farm income[a]	−0.033	0.043	0.17*
		(0.06)	(0.08)	(0.10)
	Operator age	−0.0027	0.0018	0.0021
		(0.002)	(0.003)	(0.004)
	GMO seed use[a]	0.31***	0.42***	0.24
		(0.09)	(0.14)	(0.16)
	Constant	−0.81***	−1.99***	−2.33***
		(0.16)	(0.20)	(0.27)
Corrected (OLS) Equation	Variable production cost (per acre)			
	No-till[a]	−12.99**	−11.29**	−10.90**
		(5.55)	(5.35)	(5.50)
	Irrigated[a]	39.57***	41.10***	43.16***
		(8.78)	(9.39)	(9.31)
	Yield goal	0.59***	0.56***	0.55***
		(0.06)	(0.06)	(0.06)
	Mountain[a]	−28.55	−25.84	−21.28
		(17.38)	(19.65)	(19.27)
	Southeast[a]	88.53***	84.35***	89.47***
		(13.78)	(13.44)	(13.80)
	Corn Belt[a]	44.68***	40.91***	41.63***
		(11.23)	(11.78)	(12.36)
	Northern[a]	−24.23**	−23.47**	−21.17*
		(11.04)	(11.59)	(12.17)
	Appalachian[a]	46.42***	35.65***	40.80***
		(13.04)	(13.54)	(14.00)
	Lake States[a]	63.76***	55.49***	58.93***
		(11.64)	(12.02)	(12.39)
	Northeast[a]	141.01***	135.44***	138.67***
		(12.24)	(12.52)	(12.81)
	Constant	88.77***	127.19***	132.36***
		(14.18)	(13.62)	(13.89)

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Standard errors are in parentheses. Superscript [a] indicates dummy variables equal to 1 if yes, 0 otherwise.
Source: ERS analysis of USDA Agricultural Resource Management Survey (ARMS) data.

Regional dummy variables are all significant except for the Mountain region, reflecting regional differences in cost impacts of these precision technologies relative to the omitted Delta regional dummy. These dummies have similar sizes across technology adoption nested models, but again are quite different across regions, as expected. The stability and robustness of the estimated coefficients when soil maps or soil maps and VRT are used indicates that these technologies are being used for corn production under a range of regional conditions.

Mechanics of Scenario 2 Adoption: Monitor to Mapped Soil Testing to VRT

This scenario models the inclusion of GPS-based soil properties maps in place of the yield maps used in scenario 1. Different soil types are often associated with specific nutrient deficiencies; baseline soil types can be downloaded from the USDA's NRCS web soil survey (http://websoilsurvey.nrcs.usda.gov). The grid sizes on these digitized maps differ for different parts of the country with, for example, the Eastern Shore of Maryland having on average 1.5 acres per grid and Iowa 3 to 4 acres per grid. Soil types help predict nutrient movements in soils and can complement soil nutrient maps for VRT calibration. More detailed georeferenced soil nutrient levels can be obtained from various soil tests. Soil properties change more slowly than soil nutrient levels and are often preferred for creating soil maps for this reason, but ideally properties and nutrient levels are complementary information both reflected on soil maps.

Adoption Scenario 3: Monitor to Guidance Systems to VRT

The final scenario considered is one in which the two most popular PA technologies, YM and auto-guidance systems (GSYS), are used together in combination with VRT. This scenario is designed to see whether the sequential adoption hypothesis leading to VRT holds up if PA technologies that might work just as well independently of each other, and without VRT, are used. Navigation aids like GSYS are GPS-based, aiding field operation accuracy, and can be useful for farmers implementing VRT because they can increase VRT application accuracy. Field operators using GSYS have timely, accurate location determinations within inches of their actual location on-the-fly in the field.

Figure 5 shows that adoption of YM (43%) and GSYS (27%) is taking place fairly rapidly. Almost half of farmers that have adopted YM (20% of total) have also adopted GSYS. As discussed, data collection for YM became standard practice on many combines in the late 1990s, but while GSYS hardware may be in place on most new tractors, operating GSYS requires a GPS receiver. The most accurate GPS systems are the most expensive. Real Time Kinematic (RTK)-based GPS systems are advertised to be accurate to within a few inches and cost between \$15,000 and \$20,000 in 2010.[8] Other GPS systems might be six to eight inches off at some locations depending on the system, but these systems cost much less.

GSYS provides cost savings by avoiding overlapping sprays of fertilizers and pesticides and better seeding cut-off control that can improve harvesting with fewer problems from overlapped planting that can lead to corn stalks grown too closely together, resulting in combine malfunctions. It is also easier to stay on narrow corn rows (50 centimeters or less) with a GSYS. Service providers appear to be making widespread use of GSYS with retail crop input agricultural dealership surveys indicating that GSYSs are being adapted for specialized tasks in custom work, including links and feedbacks for VRT fertilizer and chemical field work where the GSYS provides information to adjust VRT settings (Whipker and Erickson, 2011, with updates at http://agribusiness.purdue.edu/precision-ag-survey). These developments could increase the ability of any adopting tractor operator to monitor several, possibly interacting, PA systems at the same time.

Except for manual-steer light-bar systems, most GSYSs can collect and recover GPS geolocation and elevation data that can be used to implement VRT controls. The other scenarios had some type

[8] This information derives from agricultural GPS-system vendor company catalogs.

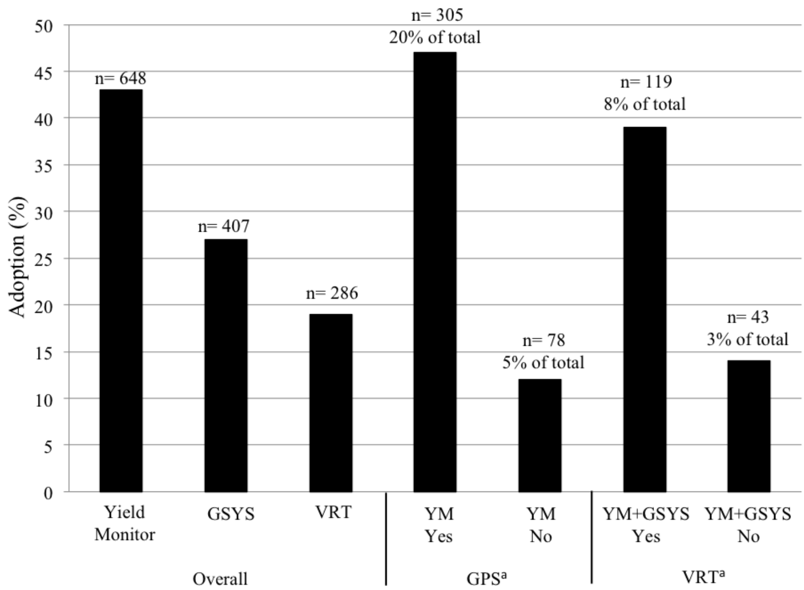

Figure 5. Scenario 3: Joint Adoption of PA Technologies[a] (GSYS if Yield Monitor, VRT if Yield Monitor and GSYS, $n = 1,507$)

Notes: YM = Yield Monitor; GSYS = Guidance Systems; VRT = Variable Rate Technology.
[a]Adoption percentages statistically different at 99% confidence level.
Source: 2010 USDA Agricultural Resource Management Survey (ARMS)

of GPS mapping before VRT implementation and some form of mapping of georeferenced data is usually required for VRT, although there are cases where VRT has been adopted manually without maps. While GSYS provides no additional data beyond location, figure 5 shows that over 35% of corn farmers that had adopted YM and GSYS (8% of total) went on to use VRT.

Batte and Ehsani (2006) show possible cost savings from using GSYS and indicate that the presence of a GPS system for GSYS can contribute to VRT adoption. The same GPS system used by a GSYS can usually be used for VRT control of application equipment. Shockley and Dillon (2008) find that auto-guidance often decreases overlapping input applications while increasing operational speed. Baio (2012) evaluates cost savings from GSYS in direct comparison to manual operation in Brazilian sugar cane. Significant McNemar results for differences in mean adoption percentages in figure 5 argue for sequential adoption of yield monitoring, GSYS, and VRT technologies. The next section considers whether these potential cost savings are actually realized in aggregate for U.S. corn producers.

Scenario 3 Results: Monitor to Guidance Systems to VRT

Estimates of the impact of the selection variables on GSYS and VRT adoption representing sequential steps in technology adoption for this scenario are presented in table 4. The results for YM adoption are the same as for scenario 1 and are shown for comparison. The treatment-effects model is estimated again using the same sets of variables used for the previous scenarios. The estimated variable cost savings for YM and GSYS used together is \$14.98/acre, which is greater than YM (\$14.50/acre) and YM/GPS soil mapping (\$13.45/acre) in the previous scenario but less than the previous YM+GPSsoil+VRT (\$20.56/acre). Guidance and VRT together are not significant in this scenario (\$11.01/acre), indicating no significant additional cost saving from the implementation of VRT with YM and GSYS. The addition of VRT was significant in both of the other scenarios. Some of the popularity of GSYS might be related more to ease of multitasking, reduced fatigue, and improved timing of operations (longer hours), which would impact profits more than costs.

Table 4. Treatment-Effects Model—Maximum Likelihood Estimates for Guidance Systems ($n = 1,507$)

Variables		Entry Adoption (Yield Monitor/YM)	Intermediate Adoption (YM + Guidance System)	Advanced Adoption (YM + Guidance + VRT)
Wald Treatment Test	Technology adoption cost effect	−14.50**	−14.98**	−11.01
		(5.94)	(6.16)	(6.90)
Akaike Information Criterion (AIC)/N		12.91	12.53	12.13
Selection (Probit) Equation	Yield Monitor, Yield Map, VRT[a]			
	Acres farmed	0.00012***	0.00017***	0.000076***
		(0.000013)	(0.000015)	(0.000020)
	Higher education[a]	0.22***	0.31***	0.30***
		(0.06)	(0.07)	(0.09)
	Soil testing[a]	0.21***	0.24***	0.28***
		(0.06)	(0.07)	(0.09)
	Off-farm income[a]	−0.033	0.0073	0.07
		(0.06)	(0.08)	(0.10)
	Operator age	−0.0027	−0.0029	−0.00019
		(0.002)	(0.003)	(0.004)
	GMO seed use[a]	0.31***	0.40***	0.27*
		(0.09)	(0.14)	(0.15)
	Constant	−0.81***	−1.60***	−2.04***
		(0.16)	(0.22)	(0.27)
Corrected (OLS) Equation	Variable production cost (per acre)			
	No-till[a]	−12.99**	−13.30**	−12.15**
		(5.55)	(5.53)	(5.61)
	Irrigated[a]	39.57***	43.75***	39.36***
		(8.78)	(8.88)	(8.92)
	Yield goal	0.59***	0.58***	0.57***
		(0.06)	(0.06)	(0.06)
	Mountain[a]	−28.55	−28.45*	−24.57
		(17.38)	(16.68)	(17.96)
	Southeast[a]	88.53***	91.11***	86.71***
		(13.78)	(13.76)	(13.72)
	Corn Belt[a]	44.68***	44.12***	37.74***
		(11.23)	(11.39)	(11.35)
	Northern[a]	−24.23**	−24.16**	−25.37**
		(11.04)	(11.39)	(11.60)
	Appalachian[a]	46.42***	45.28***	37.73***
		(13.04)	(13.36)	(13.37)
	Lake States[a]	63.76***	63.49***	56.33***
		(11.64)	(11.71)	(11.62)
	Northeast[a]	141.01***	145.64***	135.68***
		(12.24)	(12.29)	(12.36)
	Constant	88.77***	114.23***	131.07***
		(14.18)	(13.76)	(13.57)

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. Standard errors are in parentheses. Superscript [a] indicates dummy variables equal to 1 if yes, 0 otherwise.
Source: ERS analysis of USDA Agricultural Resource Management Survey (ARMS) data.

Acres (farm size), farmer education, soil test (not necessarily geolocated for mapping), and genetically modified seed use are positive and significant selection variables in all three scenario 3 models. The coefficients on soil test increase with more technology as would be expected with better soil nutrient information adding to technology adoption. Off-farm income and operator age are not significant in the selection equations, indicating that these factors do not increase the selection of these technologies.

For all corn farmers, yield goal and irrigation were both positive and significant in the corrected regression as for scenarios 1 and 2 (results sections above) after controlling for adoption of the scenario 3 technologies. The increase in aggregate variable costs associated with an increase in yield goal, after accounting for the PA technologies, is about the same as in scenarios 1 and 2. As in previous scenarios, no-till is negative and significant across technologies and has about the same-sized cost impact. No-till reduces the number of times equipment has to pass over the field, lowering machinery costs. The main difference in the regional dummy variables is that the Mountain region is significant in the YM and GSYS (intermediate adoption) equation in this scenario for the first time.

Mechanics of Scenario 3 Adoption: Monitor to Guidance Systems to VRT

As discussed, there is less logical support for adopting this set of precision technologies sequentially because YM and GSYS can probably stand alone as cost-reducing information technologies. The Wald statistics in the previous section indicate cost savings from YM and GSYS when adopted together but insignificant savings when both are adopted with VRT. This may be due to the lack of complementarity between YM, GSYS, and VRT, as YM and GSYS probably provide less useful information for VRT that relies on input information, like fertilizer and chemical application data. In company field tests, GSYS improves operations on narrow rows, accurate row cut-offs, and fewer overlapping applications but may not provide much useful information to inform VRT.[9]

Several equipment re-sale and internet auction sites were examined for specific equipment included with the tractors being sold. Generally, used tractors for sale with GPS satellite navigation were new in 2009 to 2011 and their sizes were roughly evenly distributed between 200 and 600 horsepower. This partial evidence may suggest that the observed adoption rates for GSYS could be related to the ages of tractors in use and have less to do with tractor sizes. Many more used tractors of all sizes are listed as being GPS navigation ready, where a purchaser is left only to select a GPS system.

Conclusions

Having tested multiple adoption scenarios for cost differences among PA adopters and non-adopters, our results offer evidence for the mixed adoption trends seen for different precision technologies. The three scenarios (one base technology and six combinations of other technologies) represent plausible pathways for producers to move from entry-level to intermediate to advanced adoption of PA. While six of the seven PA combinations investigated show cost savings, only one of three "advanced" combinations (i.e., including VRT) showed an additional cost savings relative to the "intermediate" combinations. VRT added savings to soil mapping and yield monitoring. Variable per acre cost savings grew from $13.45/acre (the lowest level of significant savings in any of the scenarios) to $20.56/acre under this scenario. The highest cost savings for any individual combination of PA technologies was for yield monitoring and yield mapping at $25.01/acre. One reason that VRT may not show consistent cost savings is that VRT can lead to increases in inputs and costs in situations where it is possible to increase output and profit; this could be quite possible when certain inputs are limiting output rather than when inputs are over applied.

The observed consistency of independent variable estimates not only demonstrates a robust modeling strategy but also constructs a profile of the PA adopter. A treatment-effects modeling

[9] This information derives from agricultural GPS-system vendor company catalogs.

strategy provides joint estimates of three things: factors explaining adoption, the overall impact of adoption on cost (Wald-type test), and factors explaining cost differences across all farmers in an adoption-corrected equation. Estimates for the different explanatory variables are stable across the adoption scenarios considered. Larger farms with better educated operators that perform any soil nutrient tests and use GMO seeds are found to select PA technologies. Corn farmers using no-till practices in northern regions (relative to the Delta) saw cost advantages relative to aggregate U.S. variable corn production costs (across adopters and non-adopters) after controlling for precision technology adoption. Since the adoption rates for these PA technologies are low, the farmers using these technologies are early adopters gaining experience with technologies that in the future may have more clearly defined boundaries for achieving input cost savings and may be easier to install and maintain. Future adopters may actually benefit in cost savings from lessons learned by these producers both in terms of how to save input costs using the PA technologies and which technologies work best together in different circumstances.

[Received January 2015; final revision received October 2015.]

References

Aldana, U., J. D. Foltz, B. L. Barham, and P. Useche. "Sequential Adoption of Package Technologies: The Dynamics of Stacked Trait Corn Adoption." *American Journal of Agricultural Economics* 93(2011):130–143.

Baio, F. H. R. "Evaluation of an Auto-Guidance System Operating on a Sugar Cane Harvester." *Precision Agriculture* 13(2012):141–147. doi: 10.1007/s11119-011-9241-6.

Batte, M. T., and M. R. Ehsani. "The Economics of Precision Guidance with Auto-boom Control for Farmer Owned Agricultural Sprayers." *Computers and Electronics in Agriculture* 53(2006):28–44. doi: 10.1016/j.compag.2006.03.004.

Bramley, R. G. V. "Lessons from Nearly 20 Years of Precision Agriculture Research, Development, and Adoption as a Guide to its Appropriate Application." *Crop and Pasture Science* 60(2009):197–217. doi: 10.1071/CP08304.

Bullock, D. S., M. L. Ruffo, D. G. Bullock, and G. A. Bollero. "The Value of Variable Rate Technology: An Information-Theoretic Approach." *American Journal of Agricultural Economics* 91(2009):209–223. doi: 10.1111/j.1467-8276.2008.01157.x.

Byerlee, D., and E. H. de Polanco. "Farmers' Stepwise Adoption of Technological Packages: Evidence from the Mexican Altiplano." *American Journal of Agricultural Economics* 68(1986):519–527. doi: 10.2307/1241537.

Davey, K. A., and W. H. Furtan. "Factors that Affect the Adoption Decision of Conservation Tillage in the Prairie Region of Canada." *Canadian Journal of Agricultural Economics* 56(2008):257–275. doi: 10.1111/j.1744-7976.2008.00128.x.

D'Emden, F. H., R. S. Llewellyn, and M. P. Burton. "Factors Influencing Adoption of Conservation Tillage in Australian Cropping Regions." *Australian Journal of Agricultural and Resource Economics* 52(2008):169–182. doi: 10.1111/j.1467-8489.2008.00409.x.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans. "Farm-Level Effects of Adopting Herbicide-Tolerant Soybeans in the U.S.A." *Journal of Agricultural and Applied Economics* 34(2002):149–163. doi: 10.1017/S1074070800002200.

Fleming, K. L., D. G. Westfall, D. W. Wiens, and M. C. Brodahl. "Evaluating Farmer Defined Management Zone Maps for Variable Rate Fertilizer Application." *Precision Agriculture* 2(2000):201–215. doi: 10.1023/A:1011481832064.

Fountas, S., S. Blackmore, D. Ess, S. Hawkins, G. Blumhoff, J. Lowenberg-Deboer, and C. G. Sorensen. "Farmer Experience with Precision Agriculture in Denmark and the US Eastern Corn Belt." *Precision Agriculture* 6(2005):121–141. doi: 10.1007/s11119-004-1030-z.

Griffin, T. W., C. L. Dobbins, T. J. Vyn, R. J. G. M. Florax, and J. M. Lowenberg-DeBoer. "Spatial Analysis of Yield Monitor Data: Case Studies of On-Farm Trials and Farm Management Decision Making." *Precision Agriculture* 9(2008):269–283. doi: 10.1007/s11119-008-9072-2.

Horowitz, J., R. Ebel, and K. Ueda. "No-Till Farming Is a Growing Practice." Economic Information Bulletin 70, U.S. Deptartment of Agriculture, Economic Research Service, Washington, DC, 2010. Available online at http://www.ers.usda.gov/media/135329/eib70.pdf.

Imbens, G. W., and J. M. Wooldridge. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47(2009):5–86. doi: 10.1257/jel.47.1.5.

Isik, M., M. Khanna, and A. Winter-Nelson. "Sequential Investment in Site-Specific Crop Management under Output Price Uncertainty." *Journal of Agricultural and Resource Economics* 26(2001):212–229.

Lambert, D. M., B. C. English, D. C. Harper, S. L. Larkin, J. A. Larson, D. F. Mooney, R. K. Roberts, M. Velandia, and J. M. Reeves. "Adoption and Frequency of Precision Soil Testing in Cotton Production." *Journal of Agricultural and Resource Economics* 39(2014):115–132.

Leathers, H. D., and M. Smale. "A Bayesian Approach to Explaining Sequential Adoption of Components of a Technological Package." *American Journal of Agricultural Economics* 73(1991):734–742. doi: 10.2307/1242825.

Magri, A., H. M. van Es, M. A. Glos, and W. J. Cox. "Soil Test, Aerial Image and Yield Data as Inputs for Site-specific Fertility and Hybrid Management Under Maize." *Precision Agriculture* 6(2005):87–110. doi: 10.1007/s11119-004-0687-7.

Miao, Y., D. J. Mulla, and P. C. Robert. "Spatial Variability of Soil Properties, Corn Quality and Yield in Two Illinois, USA Fields: Implications for Precision Corn Management." *Precision Agriculture* 7(2006):5–20. doi: 10.1007/s11119-005-6786-2.

Pringle, M. J., A. B. McBratney, B. M. Whelan, and J. A. Taylor. "A Preliminary Approach to Assessing the Opportunity for Site-specific Crop Management in a Field, using Yield Monitor Data." *Agricultural Systems* 76(2003):273–292. doi: 10.1016/S0308-521X(02)00005-7.

Roberts, R. K., B. C. English, J. A. Larson, R. L. Cochran, W. R. Goodman, S. L. Larkin, M. C. Marra, S. W. Martin, W. D. Shurley, and J. M. Reeves. "The Variable-Rate Input Application Decision for Multiple Inputs with Interactions." *Journal of Agricultural and Resource Economics* 31(2006):391–413. Available online at http://econpapers.repec.org/article/agsjlaare/8616.htm.

Robertson, M. J., R. S. Llewellyn, R. Mandel, R. Lawes, R. G. V. Bramley, L. Swift, N. Metz, and C. O'Callaghan. "Adoption of Variable Rate Fertiliser Application in the Australian Grains Industry: Status, Iissues and Prospects." *Precision Agriculture* 13(2012):181–199. doi: 10.1007/s11119-011-9236-3.

Schimmelpfennig, D., and R. Ebel. "On the Doorstep of the Information Age: Recent Adoption of Precision Agriculture." Economic Information Bulletin 80, U.S. Deptartment of Agriculture, Economic Research Service, Washington, DC, 2011. Available online at http://purl.fdlp.gov/GPO/gpo15242.

Shockley, J. M., and C. R. Dillon. "Cost Savings for Multiple Inputs with Swath Control and Auto-Guidance Technologies." In R. Khosla, ed., *Precision Agriculture, Proceedings of the 9th International Conference on Precision Agriculture,* Denver, CO: Colorado State University, 2008.

Stata. *Stata Glossary and Index, release 13*. College Station, TX: Stata Press, 2013.

Tey, Y. S., and M. Brindal. "Factors Influencing the Adoption of Precision Agricultural Technologies: A Review for Policy Implications." *Precision Agriculture* 13(2012):713–730. doi: 10.1007/s11119-012-9273-6.

Tozer, P. R. "Uncertainty and Investment in Precision Agriculture – Is It Worth the Money?" *Agricultural Systems* 100(2009):80–87. doi: 10.1016/j.agsy.2009.02.001.

Whipker, L. D., and B. Erickson. "The State Of Precision Agriculture 2011." 2011. Available online at http://www.croplife.com/equipment/precision-ag/the-state-of-precision-agriculture-2011/.