2018

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Journal of Agricultural and Applied Economics, 50, 1 (2018): 81–103
 doi:10.1017/aae.2017.23

CROP PRODUCTION COSTS, PROFITS, AND ECOSYSTEM STEWARDSHIP WITH PRECISION AGRICULTURE

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Abstract. Ecosystem stewardship is an important goal of crop production management. The developing question has been the feasibility and profitability of best management practices (BMPs) associated with stewardship goals. Treatment-effects empirical estimates show that soybean crop ecosystem stewardship is likely to benefit from precision agriculture's (PA) information technologies to varying degrees. After accounting for the effect of overhead expenditures on technology adoption, and input costs on operating costs and profits, we show PA technologies also affect at least six BMPs. In one comprehensive framework, PA technologies affect profits, and improve crop production management through BMPs, with benefits for ecosystem stewardship.

Keywords. Crop production, information technologies, on-farm ecosystem stewardship

JEL Classifications. Q16, O33

1. Introduction

When crop production goals are considered alongside ecosystem stewardship, the best practices for meeting those goals usually include some combination of appropriate land use, maintenance of air and water quality, avoiding overapplication of production inputs, and reducing energy use and production of greenhouse gases (Gibbs et al., 2015; National Research Council, 2010). Differences between guidelines from various sources for crop production ecosystem stewardship led Sydorovych and Wossink (2008) to use conjoint

Thanks to my branch chief, Jim MacDonald, and the rest of the Resources and Rural Economics Division management team including Cindy Nickerson and Marca Weinberg. Thanks also to conference participants at the Global AgInvesting Tech Week in San Francisco, June 22–24, 2015, and Ryan Williams of Information Services Division at Economic Research Service (ERS) for valuable research assistance. The article uses confidential U.S. Department of Agriculture (USDA), National Agricultural Statistics Service data from the Agricultural Resource Management Survey. The views expressed are those of the author and should not be attributed to the ERS or USDA.
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analysis to identify common viewpoints from different stakeholders on the definition of this and related concepts.

An open question for agricultural production has been whether farmers will find production best management practices (BMPs) profitable, including adoption of conservation tillage (Pittelkow et al., 2015) and erosion control (Montgomery, 2007), cover crops, and crop rotations. These practices have been used with production targets for decades and may benefit on-farm ecosystem stewardship while maintaining crop production profitability. Other practices being used to reach production and stewardship goals include nutrient-level monitoring (Laboski and Peters, 2012) to help limit per acre costs for nutrients, scouting for weeds (Tillman et al., 2002), and custom application of pesticides by experts (Castle and Naranjo, 2009; Conley et al., 2007).

The objective of this study is to consider if crop production ecosystem stewardship making use of BMPs in soybean production, as discussed by Conley and Santini (2007), is likely to benefit from precision agriculture's (PA) information technologies. The hypotheses tested are whether there are significant statistical correlations between BMP use and the use of PA. Hypotheses also tested whether these relationships continue to exist in an empirical model that uses BMPs in a financial framework that includes input costs, overhead expenses, soil variability, and farm size. The PA technologies considered are Global Positioning System (GPS) mapping of crop yields and soil characteristics, guidance systems that autonomously steer tractors and harvester combines, and variable-rate input application technologies (VRTs) (Miller, Griffin, and Bergtold, 2016). This set of objectives and hypotheses does not lead to estimates of the value of ecosystem services provided by BMPs but does indicate how PA is associated with stewardship BMPs.

PA technologies were originally developed to help farmers improve agricultural management through intensive management of farm production inputs to reduce costs (Feinerman and Voet, 2000; Schimmelpfennig, 2016). Recent data show that when using PA in crop production, access to more detailed production information influences farming practices that on average positively benefit the farm ecosystem. The value of environmental improvement and resource conservation is not quantified, but links between PA adoption, costs and profits, and BMPs are shown to exist.

These results extend studies like the one by Larkin et al. (2005), which shows that farmers in the southeastern United States perceive an improvement in environmental quality from adopting PA on larger farms, when PA is more profitable, and when they are concerned with reducing production inputs. Baumgart-Getz et al. (2012) develop a meta-analysis from the literature on the adoption of BMPs and farmer characteristics that influence adoption.

Making a stronger link between PA information technologies and production stewardship is important as it could be coming at a time when consumers, especially in developed countries, are becoming more concerned about how their food is made, and some are willing to pay for identity preservation and sustainability labeling for organic products (Reganold and Wachter, 2016). Fair trade, carbon footprint, and food supply-chain ecocertification have also caught consumers' attention (Onozaka and Mcfadden, 2011; Teisl, Roe, and Levy, 1999). The article makes the case for a connection between PA and stewardship by taking a close look at PA adoption and how it relates to on-farm soil variability, along with an analysis of farm financial data linked to soybean production.

Industry organizations are reacting to the increased emphasis on stewardship by working to standardize BMPs. The American Society of Agricultural and Biological Engineers (ASABE, 2016) issued a draft standard, "Framework for Sustainable Agriculture" (X629) to standardize BMPs and improve key performance indicators in agricultural production systems. When finalized, X629 may be designated an American National Standards Institute standard or an International Organization for Standardization standard, or possibly both. ASABE has a committee for crop production systems, machinery, and logistics (MS49) and a committee to foster the development and adoption of PA (MS54). To evaluate standards already being used in soybean production, the National Sustainable Soybean Initiative (NSSI) surveyed more than 1,500 soybean farms in Wisconsin using the most exhaustive set of practices that have been evaluated. Dong et al. (2015) analyze the survey results, and example questions and summary statistics are also available (Knuteson et al., 2013).

This article evaluates the national prevalence of ASABE- and NSSI-identified BMPs, using a national survey linked to the U.S. Department of Agriculture's (USDA) Census of Agriculture data. National coverage of these BMPs is constructed from USDA's 2012 Agricultural Resource Management Survey (ARMS) of soybean producers. Using the organization of the NSSI survey, analogous practices surveyed in ARMS have been grouped into five categories, including soil care for soil health, nutrient control to avoid overapplications, monitoring of fields for pests to allow early interventions, between-season field operations planning, and long-term written plans. The prevalence of BMPs is then linked to the use of PA technologies.

2. Correlations between Soybean BMPs and Adoption of PA

This section discusses the stewardship practices in detail and checks for simple correlations between the practices and individual PA technologies. Soil care is defined as the use of conservation tillage and erosion control (Table 1) and includes reduced tillage that can decrease soil erosion and improve soil health by increasing the diversity of soil microbes and microfauna, while lowering oxidation of soil organic matter; 52% of all U.S. soybean fields use soil conservation practices.

Table 1. Sustainable Farming Practices More Common When Precision Agriculture in Use

Sustainable Farming Practice	GPS Soil/Yield Mapping	Guidance System	VRT	Percent of All Soybean Fields Using Practice
	(Entries with an asterisk show the differences in practice adoption rates between farms with precision agriculture technologies and farms that do not have the technologies.)			
Soil care practices				
No-till, reduced till, or other soil conservation tillage practice	8%*	11%*	9%*	52
Contours, grass buffers, terraces, or other erosion control structure	6%*	8%*	5%*	34
Nutrient control practices				
Soil phosphorus/nitrogen nutrient test done or plant tissue test	9%*	6%*	12%*	18
Crops rotated	20%*	11%*	9%*	48
Field condition monitoring				
Scouting for weeds by consultants (on farms with high soil variability)	5%*	6%*	4%*	3
Scouting for weeds by consultants (low variability)	5%*	12%*	5%*	6
Interseasonal field operations planning				
Hiring technical services for changing soil, nutrient, or pest management practices	8%*	10%*	8%*	11
Changing cropping practices to reduce fertilizer use	9%*	7%*	17%*	23
Long-term written planning				
Plan for conservation, nutrients, pest management, or irrigation	6%*	10%*	5%*	19
Ten-year plan in place	13%*	18%*	20%*	42

Notes: High and low soil variability calculated from the National Commodity Crop Productivity Index. The index is measured on Common Land Units, which approximate farmer's individual fields within a 3 km radius. Surveyed farmers are not asked, by law, to reveal the geolocated boundaries of the individual field used for survey responses. "All soybean fields" are derived from National Agricultural Statistics Service survey weights that show nationally representative statistics for all data collected. Asterisk (*) indicates 98% confidence of significant difference in mean percentages with and without each individual precision technology. Comparison of means by two-sample *t*-statistics using sample calculated standard deviations. GPS, Global Positioning System; VRT, variable rate input application technology.

Soil services can be linked to farm ecosystems that can affect crop production (Cernansky, 2016; Jónsson and Davíðsdóttir, 2016). Soil organic matter and fertilizer can help lower the risk of diseases like soybean cyst nematode (Bao et al., 2013). The highest association for reduced tillage is with guidance (11%), which improves field operation accuracy when crop rows may not have traditional plow furrows and are thus less well defined. Operation accuracy can also help reduce subsoil compaction from implement drift, while maintaining desired row spacing. Knowler and Bradshaw (2007) link effective soil conservation to site-specific “particular conditions” (p. 25). Delgado and Berry (2008) call this “precision conservation” and note its origins in models of erosion, “spatial data mining, and map analysis” (p. 1). This links detailed information on soil conditions, like those made available by GPS soil maps, to the effective use of conservation tillage.

Erosion control structures (Table 1) also have the highest association with guidance (8%), possibly because field operations that go off-target and into erosion control areas might be highly unproductive. Guidance also helps farmers operate around erosion control structures and plantings. Grass buffers most often, but also contours and terraces, have been used to complement conservation tillage to maintain soil quality. Reimer et al. (2012) consider grassed waterways and filter strips as BMPs for soil erosion control, and they find that “information availability” (p. 127) influence outcomes. Georeferenced soil maps are often a good source of this type of information.

2.1. Best Practices for Nutrients

This analysis splits nutrient testing as a BMP from soil mapping that is a common tool for PA. There is some overlap between testing and mapping nutrients and soil characteristics. Phosphorous (P) and potassium (K) levels are often mapped, but usually not on the same map with soil characteristics. Soil nitrogen is difficult to measure because of its link to temperature and soil moisture; consequently, is it hard to map, but soil organic matter maps are often used to create nitrogen (N) application prescriptions for PA. Farmers may grid sample many macro- (N, P, and K) and micronutrients, but many save costs by grid sampling only P, K, organic matter, and pH.

Remotely sensed data on leaf reflectance can help monitor plant stress, and these data can be mapped but would not be considered a soil map. Nutrient tests are discussed as BMPs in the literature, and a few studies mention PA. Kropff, Bouma, and Jones (2001) stress spatial and temporal dimensions in stewardship, and Fountas et al. (2006) develop decision-making processes in information-intensive practices for PA. Fuglie and Kascak (2001) explicitly model soil nutrient tests as a BMP. Table 1 shows correlations between nutrient/plant tests and the PA technologies. It shows that nutrient tests are most strongly associated with VRT, which might be expected because VRT applies nutrients at variable rates.

Crop rotations (Table 1) are commonly used to improve crop productivity and may also benefit soil stewardship. Roughly half of all soybean fields rotated crops, and usually, this is soybeans with corn. Crop rotation has a higher association with mapping and guidance than with VRT and is often used to maintain beneficial soil nutrient and micronutrient levels; improve soil structure, which aids soil microbial community structure and level of activity; and improve soil organic matter chemistry. The resulting soil nutrient levels then can be geolocated on GPS soil maps.

2.2. *Best Practices for Field Monitoring*

Alongside nutrient tests, a key information input that influences farmer production practices comes from crop consultants (see fig. 2 in Fountas et al., 2006) and expert opinion (Kropff, Bouma, and Jones, 2001). Weed consultants (Table 1) in particular often offer program packages that include three or more farm scouting visits, including at least two early in the season when farmers can address problems most easily. In addition, scouts often walk fields to check for weeds before spraying. This can help identify crop growth stages when spraying can provide the most benefit.

2.3. *The Role of Long-Term Planning in Production Stewardship*

The bottom sections of Table 1 consider progressively longer-term consultation and planning of farm production operations. Interseasonal field operations planning covers circumstances beyond diagnosis of specific day-to-day production problems. Consultant input up to this point has reflected the need to respond to within-season changes in weather, pest pressures, or other unforeseen events. Interseason planning of nutrient applications has its largest association with guidance, but mapping and VRT are almost as substantial. There is also a strong association between VRT and reduced nutrient use. The implication of this is that farmers may be requesting that input retailers help them to apply recommended amounts of fertilizer, accurately, and at the appropriate time—supplementing the efforts of nutrient application professionals discussed in the next section.

In regard to long-term written planning, Sorensen et al. (2010) focus on the interaction of strategic and whole-farm planning with a "future farm vision" using "long-term farm and production information" (p. 49). Long-run considerations play a central role in their "user-centric" model. The results at the bottom of Table 1 are consistent with this, showing that VRT is most highly associated with 10-year planning (20%), with guidance close behind (18%). Both of these results are partially explained by the capital requirements needed for the technologies and the need to spread these capital costs over a number of operating years.

2.4. *Cover Crops and Biocontrols with PA*

Despite the popularity of cover crops and biocontrols with the Natural Resource Conservation Service (USDA) (Council on Food, Agricultural & Resource Economics and USDA Economists Group, 2017) and some USDA extension agents, the use of both of these practices is limited in U.S. soybean production. The focus here is on short-term cover crops like winter rye or clover, planted between periods of regular crop production to prevent erosion, to increase soil organic matter and nitrogen content. Longer-term plantings like alfalfa and perennial grasses are usually kept in place for several years to prevent soil erosion and improve soil quality, and they may be harvested several times for livestock feed or used as forage. Short-term cover crops can provide compaction reduction, soil aeration, and water infiltration, but only a few farmers planted them. Cover crops may be seen as costly in terms of the seed and planting cost with little offsetting salable product.

Biocontrols make use of beneficial organisms to help manage pests but are used on only roughly 6% of all soybean fields. There are statistically significant higher rates of use of biocontrols only with VRT adoption (10% vs. 2%). Future work will investigate whether new seed inoculants that contain biopesticidal properties might also be associated with adoption of GPS maps, guidance, and VRT.

To summarize Table 1, it shows that all three of the precision technologies, GPS mapping, guidance steering, and VRT, are associated with a significant increase in each subgroup of sustainable farming practices. Of the 30 possible combinations of practices and technology, 11 showed double-digit percent increases when a precision technology was in use, and an additional 8 stewardship practices had 8%–9% increases with PA.

3. Nutrient and Pesticide Costs with PA, and Measuring Soil Variability

In addition to individual practices, on-farm stewardship in soybean production could be significantly influenced by costs for fertilizer and chemicals. Proposals for controlling nonpoint-source pollution from agricultural runoff into water sources like the Chesapeake Bay have been examined (Ribaudo, Savage, and Aillery, 2014). Another objective of this article is to consider whether U.S. soybean farmers who use PA also use more or less within-year fertilizers and chemicals than those who do not use PA (Bongiovanni and Lowenberg-Deboer, 2004). To answer these questions using correlations and empirical models, it is necessary to also consider whether each individual farm has higher or lower than median variability in soil quality, and whether custom services are used.

Productive variability of the soil in a particular field can be approximated using the National Commodity Crop Productivity Index (NCCPI). The NCCPI summarizes and aggregates the information in a national soil classification system that uses the inherent capacity of different soil types to produce dryland (nonirrigated) commodity crops. The NCCPIs used in this study are developed specifically for soybeans. An inverse distance weighted (IDW) average of the index is created using all fields within 3 km of each proxy survey location because geocoordinates of the actual field surveyed are protected by confidentiality agreement. The IDW takes 1 over the distance from the proxy location squared as the denominator to create a nonlinear distance weight that gives more weight to closer soybean fields and diminishingly less to the farther ones up to the 3 km limit. In this way, the IDW gives more weight to NCCPI data that lie closer to the proxy survey location than those farther away. The result is a continuous farm soil variability index that theoretically can lie between 0 and 1. To compare

Table 2. Nutrient and Pest Control Costs by Precision Agriculture (PA) Practice

	GPS Soil/Yield Mapping	Guidance System	VRT	Total (on high- or low-variability farms)
	Average Farm Costs for Fertilizer and Pesticides by Technology			
Fertilizer costs per acre(on farms with low soil variability [l.s.v.])[a]				$58.25/acre (755,000 fields)
Yes	$57.04	$52.59	$54.73	
No	$58.80	$61.26	$59.02	
Percent difference	−3%	−14%	−7%	
Fertilizer custom application costs per acre (on farms with high soil variability [h.s.v.])[b]				$1.25/acre (745,000 fields)
Yes	$1.94	$1.72	$2.75	
No	$0.93	$1.01	$0.85	
Percent difference	110%	71%	222%	
Chemical costs (herbicide and pesticide per acre on farms with h.s.v.)[b]				$22.45/acre (745,000 fields)
Yes	$25.29	$24.61	$25.63	
No	$21.06	$21.32	$21.60	
Percent difference	20%	15%	19%	
Chemical custom application costs per acre (on farms with l.s.v.)[a]				$2.58/acre (755,000 fields)
Yes	$1.79	$2.40	n.s.	
No	$2.83	$2.68	n.s.	
Percent difference	−37%	−11%		

[a]Differences in nutrient costs and pesticide custom application costs on high-variability farms not significant and not presented. Descriptive statistics for soil variability are in Table 3.
[b]Differences in pesticide costs and nutrient custom application costs on low-variability farms not significant and not presented. Descriptive statistics for soil variability are in Table 3.
Notes: Calculated percent use of stewardship practice on farms adopting/not adopting PA technology not significantly different. Percentages not reported because comparisons might lead to spurious inferences. Percent differences between technologies in table are determined to be significant at 90% level or greater by difference of means two-tailed *t*-tests. Nutrient costs are the total cost of all nutrient and fertilizer products applied. Nutrient custom application costs do not include materials. Custom-applied nutrient materials included in nutrient costs. Likewise for pesticide materials and custom application costs. The h.s.v. and l.s.v. farms have a higher/lower than median distance-weighted soil variability index. Soil index construction discussed in the text. GPS, Global Positioning System; n.s., not significant; VRT, variable rate input application technology.
Source: USDA, Economic Research Service estimates using data from the Agricultural Resource Management Survey Phase II.

fertilizer and chemical costs (with and without custom applications), the entire sample is split evenly into high soil variability (h.s.v.) and low soil variability (l.s.v.) farms having higher/lower than median soil variability indexes (results are in Table 2).

Table 3. Descriptive Statistics for Operating Cost and Profit Variables (for Tables 4 and 5)

	Mean	Standard Deviation	Minimum	Maximum
Adoption variables				
Unpaid labor ($ total opportunity cost)	1,124	1,765	0	>35,000
Machinery and equipment ($ total of capital recovery costs)	5,881	6,748	0	>100,000
Farm soil variability index (discussed in text)	0.56	0.17	0.03	0.98
Farm size (soybean acres)	760	1,052	n.r.	n.r.
Cost/profit variables				
Operating costs	28,704	32,270	n.r.	n.r.
Operating profit	10,731	20,479	n.r.	n.r.
Seed costs ($ total)	3,767	3,840	n.r.	>57,000
Fertilizer costs ($ total)	2,390	3,981	0	>55,000
Chemical costs ($ total herbicide and pesticide)	1,819	2,457	0	>37,000

Notes: Table figures are for raw unweighted data. All other estimates in the article are calculated using data weighted for the skewed distribution of farm sizes in the raw data. n.r. indicates not reported to maintain Agricultural Resource Management Survey (ARMS) respondent confidentiality. Sample size is 2,472 observations.
Source: USDA, Economic Research Service estimates using data from the ARMS Phase II and Phase III.

Erickson and Widmar (2015) show that PA use is rising among agricultural service dealerships in the Midwest, and nutrient and pesticide practices are an important consideration for stewardship because most soybean farms would be expected to either have their own application programs or use service providers. Chemical control of resistant weeds has made economizing on herbicides a mounting challenge (Livingston et al., 2015). If farmers apply more nutrients overall, they can either use more custom services or their own equipment and labor that have fixed costs that can be spread over a larger expense base. The same for pesticides; farmers can use custom services or apply the pesticides themselves, and this might require additional equipment with fixed costs.

Nutrient tests (Table 1) for soil phosphorous and nitrogen and plant tissue tests would be used to calibrate nutrient applications, and scouting for weeds would help indicate when chemical spending might be needed. Chemical spending for insect pests has focused recently on soybean aphids and Japanese beetles in U.S. Midwest soybeans, and stinkbugs and bean-leaf beetles have been recurring pests for some time. Identifying pest patterns and cycles can help determine best treatment options.

The total (right-hand) column in Table 2 shows that on an average U.S. soybean field, farmers spend more than twice as much per acre on in-season nutrients as on pesticides. Fertilizer cost is only counted within the current year, and the results do not account for the common practice of applying phosphorus and potassium in the prior year for the next soybean crop. Custom application costs do not include the cost of materials and show the opposite relationship, with twice as much per acre spent on custom pesticide applications as on fertilizer applications. Table 2 reports results for l.s.v. and h.s.v. farms, and significant results show that all three PA technologies are associated with cost savings on fertilizer, the largest expense item, with the largest savings when using guidance ($52.59 vs. $61.29) on l.s.v. farms. Percent custom application costs of nutrients (nutrient material costs are not included because they are included in total nutrient costs) are considerably higher with PA on h.s.v. farms (only 71% with guidance), but this is on a much lower average cost per acre.

Pesticide costs show the reverse relationships between expenses and adoption of PA technologies. Pesticide costs per acre are higher with the three technologies on h.s.v. farms, and custom application costs for pesticides are lower with mapping and guidance on l.s.v. farms. There is a rationale for this opposite association between fertilizer and pesticide application expenses related to PA adoption. Because average costs per acre on nutrients are higher regardless of PA, there could be larger possible cost savings in nutrient applications over chemicals to spread over the fixed costs of purchase and installation of PA equipment.

It might be expected that both nutrient and pesticide costs, either by the farmer or custom service provider, would be higher on highly variable soil if greater diversity of soil productivity raises the diversity of problems faced. PA might also be expected to be used to help control some of these extra costs, but this is only true for fertilizer and custom-applied chemicals on l.s.v. farms. It should be noted that there is a growing emphasis with input dealerships, custom service operators, and crop specialists that advise farmers on applying needed fertilizers accurately in the recommended amounts at the right time. Higher chemical costs on h.s.v. farms with PA are probably attributable to more complete coverage of weed and pest problems with PA, and more dispersed, difficult-to-find problems in pockets of the field would be expected to be greater on h.s.v. farmland.

4. An Analytical Model and Farm Financial Data for Estimation

The model assumes farmers make farm input and production practice decisions based on their economic profit and loss situation, and results give estimated impacts of variables on farms that use PA compared with those that do not. Descriptive statistics for all the variables included in the estimated models are in Table 3. The data in the table are unweighted so that meaningful standard deviations, minimums, and maximums can be presented. All other estimates in the article are calculated using the same raw data, but weighted to represent national average values that account for the skewed distribution of farm sizes in the raw data. The data used in this study come from the 2012 ARMS of soybean producers. The ARMS is managed jointly by USDA's Economic Research Service and National Agricultural Statistics Service (NASS) and collects data annually in several phases on field-level production practices and farm-level finances for a rotating set of commodity crops. The survey provided 2,472 soybean field-level observations that are weighted by NASS to match the farm-size demographic of the census population of more than 302,000 U.S. soybean farms.

The dependent variables are total operating costs and operating profit. All input costs and all stewardship practices (discussed in Table 1), are tested as explanatory variables. Operating profit includes production output multiplied by market price or total revenue, adding in a yield effect. Overhead expenses add to production costs, and annual fixed cost allocations of these expenses could affect PA technology adoption and are tested as adoption explanatory variables. These include unpaid labor, capital service flows for machinery and equipment, the opportunity cost of land measured as the rental rate (including taxes and insurance), and land productivity converted to a measure of soil variability. Unpaid labor is commonly family labor in some kind of actual or implied partnership with the farm owner and, as such, is more appropriate as an overhead variable. Unpaid labor is an opportunity cost estimated from whole farm financial data. Attributes of unpaid operators—such as age, education, marital status, and location—are collected and used to estimate their foregone off-farm hourly earnings. Capital service flows are estimated from the useful life of the machinery or equipment item and are typically longer than expense amortization or capital depreciation used for other on-farm financial analysis. The estimated operating profit model for farmer i is as follows: Operating profit$_i$ $= f$(revenue, operating costs$_i$, production practices, and PA technology adoption), where the technology adoption equation is specified as Technology adoption = f(overhead expenses$_i$).

The operating cost dependent variable model uses all the same variables without revenue, giving a comparison of results for the same set of variables, but without a yield effect. In a profitability survey by Griffin et al. (2004), only 21% of the PA studies they reviewed included operator time, but those studies found it was significant. There are 46 NSSI questions that have analogous questions on ARMS that were used to create the stewardship variables (Table 1).

5. The Empirical Model—Treatment Effects

Production stewardship practices for soybeans are more common on farms that adopt precision technology (Table 1), and per acre use of fertilizers and chemicals is lower or higher with PA depending on whether the farm has l.s.v. or h.s.v., respectively (Table 2). Custom service application costs, likewise, vary by soil productive variability. An important question for stewardship and PA adoption is how they both affect farm profits. To determine the impact of stewardship and PA on costs and profits, factors affecting adoption like farm size (Castle, Lubben, and Luck, 2016; Fernandez-Cornejo, Daberkow, and McBride, 2001), soil variability, and other overhead items should first be held constant because they can affect stewardship and other practices that will most likely affect costs and profits.

To control the confounding variables problem, a treatment-effects model is used (Imbens and Wooldridge, 2009; Stata Corporation, 2013). This model is especially useful when observational data are fortuitously available on both types of farms—those that are treated (PA technology adopters) and untreated (nonadopters). The adoption measurement section generates fitted values (after overhead explanatory variables explain adoption) that can be used as an unconfounded variable representing each PA technology in the cost/profitability section of the model. Adoption and financial sections of the treatment-effects model are estimated simultaneously using maximum likelihood. This is the approach used by Schimmelpfennig and Ebel (2016).

This model structure requires several treatment-specific diagnostic tests. The adoption and financial equations must be tested for nonindependence, otherwise these two sections could be estimated separately without the treatment model framework. A formal test for omitted variables can also be carried out by comparing the similarity of treatment (adopters) and nontreatment groups, other than that they are PA adopters or not. They should be similar enough to reject a test of overidentification, indicating that there is sufficient explanatory power in each of the sets of covariants in the groups. Because the models for all three PA technologies use similar variables so that their estimated coefficients can be compared and contrasted, a test in which adopters and nonadopters are both correctly identified is not an easy hurdle for the model to pass.

5.1. Impacts of Overhead on PA Adoption

Adoption of PA technologies likely can affect operating costs that depend largely on input application rates, and overhead costs that depend on substitutions between capital and labor. The results show that capital/labor trade-offs are in fact the expenses that influence adoption, and input costs and sustainable practices influence operating costs and profits on farms that use PA compared with those that do not. The effects of inputs and stewardship practices are determined with changes in overhead held constant. Tests for independence of these two sets of considerations are strongly rejected, indicating that adoption influences operating costs and profits while also depending on trade-offs in the deployment of overhead. Results in Table 4 have operating costs as the dependent variable, and Table 5 shows the results for operating profit. Explanatory variables in both tables are the same, and differences in coefficient estimates provide complementary insights, with reasonable explanations for the differences.

The top section of both Tables 4 and 5 shows how overhead expenses help explain adoption. Capital investments in PA farm equipment can require loans or alter the financial structure of the farm business that can affect both its labor and other capital expenditures. Having more unpaid farm labor, which is often family labor on informal agreements that are agreed to years in advance and measured as an opportunity cost, is negatively associated with adoption of all

Table 4. Operating Cost Treatment-Effects Models—MLEs for Each Technology

	GPS Soil/Yield Mapping	Guidance System	VRT
	Coefficients Estimated Separately for Each Technology (three sets of results presented)		
Precision technology adoption			
Unpaid labor ($ total opportunity cost)	− 0.359	− 0.324	− 0.226
	(− 6.50)**	(− 6.02)**	(− 3.98)**
Machinery and equipment ($ total capital recovery costs)	0.175	0.180	n.s.
	(2.95)**	(3.05)**	
Farm soil variability index (discussed in text)	0.665	0.467	0.628
	(5.21)**	(4.12)**	(4.62)**
Farm size (soybean acres)	0.127	0.091	n.s.
	(3.10)**	(2.22)*	
Cost equation			
Precision technology (fitted values from "Precision technology adoption")	− 0.119	− 0.125	− 0.111
	(− 5.36)**	(− 5.00)**	(− 4.32)**
Seed costs ($ total)	0.578	0.578	0.578
	(55.53)**	(55.30)**	(55.47)**
Fertilizer costs ($ total)	0.220	0.220	0.220
	(31.73)**	(31.73)**	(31.84)**
Chemical costs ($ total herbicide and pesticide)	0.180	0.181	0.181
	(24.90)**	(25.22)**	(25.50)**
Conservation tillage (see Table 1)	− 0.039	− 0.040	− 0.040
	(− 3.03)**	(− 3.02)**	(− 3.05)**
Erosion control use (see Table 1)	n.s.	n.s.	n.s.
Nutrient tests carried out	0.069	0.071	0.070
(definition with Table 1)	(4.97)**	(5.07)**	(4.96)**
Crops rotated (see Table 1)	n.s.	n.s.	n.s.
Scouting for weeds by consultants (see Table 1)	0.071	0.071	0.071
	(3.30)**	(3.27)**	(3.28)**
Cropping practices adjusted to reduce fertilizer (see Table 1)	n.s.	n.s.	n.s.
Ten-year production practice plan in place (see Table 1)	n.s.	n.s.	n.s.
Constant	1.68	1.68	1.66
	(32.57)**	(32.07)**	(32.98)**
Sample size (N)	1,707	1,714	1,714

Notes: Estimated z-statistics (pseudo t-statistics) in parentheses; asterisks (**, *) indicate significant at the 99% or 90% confidence level, respectively. Included variables that are not significant are denoted n.s. Model selection based on data coherence, consistency with economic theory, parsimony of parameters, and goodness of fit (Hendry and Richard, 1982). Fit measured by Akaike and Bayesian information criteria. Farm size determined from total soybean acres on the farm. GPS, Global Positioning System; VRT, variable rate input application technology.
Source: USDA, Economic Research Service estimates using data from the Agricultural Resource Management Survey Phase II and Phase III.

Table 5. Operating Profit Treatment-Effects Models—MLEs for Each Technology

	GPS Soil/Yield Mapping	Guidance System	VRT
	Coefficients Estimated Separately for Each Technology (three sets of results presented)		
Precision technology adoption			
Unpaid labor ($ total opportunity cost)	– 0.345	– 0.311	– 0.214
	(– 5.61)**	(– 5.43)**	(– 3.52)**
Machinery and equipment ($ total capital recovery costs)	0.239	0.250	0.154
	(3.58)**	(3.98)**	(2.15)*
Farm soil variability index (discussed in text)	0.893	0.668	0.921
	(6.04)**	(5.12)**	(5.70)**
Farm size (soybean acres)	n.s.	n.s.	n.s.
Profitability equation			
Precision technology (fitted values from "Precision technology adoption")	0.602	0.670	0.610
	(4.78)**	(5.48)**	(4.66)**
Seed costs ($ total)	0.871	0.864	0.876
	(16.10)**	(16.05)**	(15.47)**
Fertilizer costs ($ total)	– 0.060	– 0.061	– 0.062
	(– 2.68)**	(– 2.76)**	(– 2.78)**
Chemical costs ($ total herbicide and pesticide)	0.152	0.154	0.159
	(3.44)**	(3.51)**	(3.60)**
Conservation tillage (see Table 1)	n.s.	n.s.	n.s.
Erosion control use (see Table 1)	– 0.098	– 0.096	– 0.099
	(– 1.67)*	(– 1.64)*	(– 1.69)*
Nutrient tests carried out (definition with Table 1)	0.1354	0.139	0.138
	(2.17)*	(2.25)*	(2.19)*
Crops rotated (see Table 1)	0.1351	0.144	0.152
	(2.40)*	(2.53)*	(2.65)*
Scouting for weeds by consultants (see Table 1)	0.137	0.132	0.144
	(1.89)*	(1.84)*	(2.02)*
Cropping practices adjusted to reduce fertilizer (see Table 1)	0.148	0.160	0.151
	(1.94)*	(2.10)*	(2.02)*
Ten-year production practice plan in place (see Table 1)	n.s.	n.s.	n.s.
Constant	1.99	1.99	1.97
	(7.88)**	(7.98)**	(7.54)**
Sample size (N)	1,647	1,653	1,653

Notes: Estimated *z*-statistics (pseudo *t*-statistics) in parentheses; asterisks (**, *) indicate significant at the 99% or 90% confidence level, respectively. Included variables that are not significant are denoted n.s. Model selection based on data coherence, consistency with economic theory, parsimony of parameters, and goodness of fit (Hendry and Richard, 1982). Fit measured by Akaike and Bayesian information criteria. Farm size determined from total soybean acres on the farm. GPS, Global Positioning System; VRT, variable rate input application technology.
Source: USDA, Economic Research Service estimates using data from the Agricultural Resource Management Survey Phase II and Phase III.

three technologies. The size of the negative effect is about the same for mapping and guidance and is smaller for VRT (Tables 4 and 5) on farms that use PA compared with those that do not. Unpaid labor is a predetermined overhead cost that could well reduce the flexibility of farm owners or managers to adopt new technologies. Machinery is usually a substitute for labor in relation to both costs and profits, and here as expected, the estimates in both tables are positive and about the same size for mapping and guidance on farms that use PA compared with those that do not. For profits (Table 5), machinery is also significant for capital intensive VRT.

The biggest impact on adoption for all three technologies in both tables comes from soil variability, with greater adoption when farm soils are more variable. All three soil variability estimates for adoption are larger for profits than costs, with VRT being the largest, on farms that use PA compared with those that do not. Farm size is positive and significant on costs for mapping and guidance, with similarly sized effects, so larger farms have adopted mapping and guidance, but not VRT. Farm size is not significant in explaining adoption of any of the three technologies on operating profitability (Table 5). This seems to indicate that yield effects of adoption do not depend on farm size for PA technologies, whereas cost effects do when comparing farms that use PA with those that do not.

5.2. Impacts of PA and Stewardship Practices on Costs and Profit

In the lower sections of both Tables 4 and 5, the "precision technology" line shows the significance of the impact of all three PA technologies on the operating costs and profits of farms that use the technology compared with those that do not, which can be taken from the fitted values. Interpretation of these coefficients requires converting them into average treatment effects on the treated, which takes into account the correlation between the top (adoption) and bottom sections (costs or profits). These percentages are discussed in Section 5.3.

The other coefficients can be discussed directly. Seed costs are positive, significant, and about the same size across PA technologies in both tables. Comparing Tables 4 and 5, seeds contribute more to profit than costs on farms that use PA technology compared with those that do not, indicating that yields are higher because "seed costs" are the same variable in both tables. Within-season fertilizer applications appear to be adding to operating costs and lowering profit, all else held constant. This could provide some aggregate evidence for overapplication of nutrients. Because not all soybean fields in the U.S. receive fertilizer, some have adequate soil fertility to reach yield goals because of previous fertilizer or manure applications. In some cases, fertilizer applications may be taking place on low soil fertility fields that are lower yielding and less profitable, and this could be the source of the negative estimated coefficient in the profit equation. Chemicals have significant and positive effects on farms that use PA compared with those that do not, for both costs and profit, leading to an interpretation for chemicals as having been used more judiciously on average

Table 6. Treatment-Effects Models—Diagnostic and Specification Statistics

	GPS Soil/Yield Mapping	Guidance System	VRT
	Coefficients Estimated Separately for Each Technology (three sets of results presented)		
Operating cost models			
Wald $\chi^2(1)$ test of independent equations (i.e., rho = 0) (Prob > χ^2)	52.52 (0.000)	37.96 (0.000)	42.26 (0.000)
Model Wald $\chi^2(3)$ test (pseudo *F*-test)	25,752.31 (0.000)	25,324.58 (0.000)	26,794.32 (0.000)
Log pseudolikelihood	−450,708.76	−499,867.99	−376,918.97
Akaike information criterion (AIC) Bayesian	901,453.5	999,772	753,873.9
(Sawa's) information criterion (BIC)	901,551.5	999,870	753,972
$\chi^2(5)$ test of overidentification for covariant balance (Prob > χ^2)	9.74 (0.083)	3.521 (0.000)	4.076 (0.000)
Operating profit models			
Wald $\chi^2(1)$ test of independent equations (i.e., rho = 0) (Prob > χ^2)	52.52 (0.000)	37.96 (0.000)	42.26 (0.000)
Model Wald $\chi^2(3)$ test (pseudo *F*-test)	25,752.31 (0.000)	25,324.58 (0.000)	26,794.32 (0.000)
Log pseudolikelihood	−450,708.76	−499,867.99	−376,918.97
AIC	901,453.5	999,772	753,873.9
BIC	901,551.5	999,870	753,972
$\chi^2(5)$ test of overidentification for covariant balance (Prob > χ^2)	6.929 (0.000)	3.586 (0.000)	4.161 (0.000)

Notes: Model selection based on data coherence, consistency with economic theory, parsimony of parameters, and goodness of fit (Hendry and Richard, 1982). Fit measured by AIC and BIC. Costs per acre calculated from acres of soybeans planted. Farm size determined from total soybean acres on the farm. GPS, Global Positioning System; VRT, variable rate input application technology.
Source: USDA, Economic Research Service estimates using data from the Agricultural Resource Management Survey Phase II and Phase III.

in soybeans than within-season nutrients. Presumably, yields and profits would be much lower without applications when they are most needed, but on average, effects of chemicals on costs and profits are quite similar on farms that use PA compared with those that do not.

Having set the stage in two ways, by accounting for the effects of overhead on adoption, and PA technology and input costs on operating costs and profits, it is possible to interpret the impacts of production stewardship practices from Tables 4 and 5. Conservation tillage is significant and lowers costs with all three PA technologies, but it is not significantly related to profits. This probably means that no-till and other soil conservation practices save costs, presumably through maintenance of soil structure and reducing soil erosion, without significantly affecting operating profit in soybean production. Erosion control has the reverse effect with a significant and negative effect on profit but none on costs. Because control measures often require taking erodible soils out of production, this result is not surprising. Detailed nutrient tests that provide more information than are usually included on GPS maps have a significant and positive effect on costs as expected, but a larger positive effect on profits. This seems to support detailed nutrient testing for soybean farm profitability, even if basic nutrient test results are being mapped with soil characteristics.

Crop rotation is common in soybean production, with about half of U.S. corn farmers reporting that they rotate their crop (Schimmelpfennig, 2016, p. 5). The estimated effect is positive and significant on profit and not significant on costs, providing supporting evidence for the widespread use of this stewardship practice. Scouting for weeds by consultants adds to costs but contributes more to profits, also supporting the use of this practice for raising yields. Reinforcing the previous result on fertilizer overapplication, when soybean farmers indicate that they adjusted practices to reduce fertilizer use, their profits were positively and significantly affected, whereas their costs were not. Finally, after controlling for all these factors, it might still be expected that long-range (10-year) planning might affect costs or profits, but this is not the case. One explanation would be that long-range planning is difficult to discern in 1 year of data (2012).

5.3. Model Diagnostic and Specification Tests

There are several standard diagnostic tests for treatment models. The first is a Wald test for independent equations (Table 6) that show if the adoption and cost/profitability sections of the model for each precision technology are *not* independent. This test is a χ^2 test of rho equal to zero that is rejected at high levels of significance (P values close to zero), indicating the presence of confounding effects needing to be controlled between adoption and cost/profitability by treatment effects. The other Wald test reported is analogous to an F-test of joint significance of the variables, rejecting the possibility that the estimated coefficients are jointly equal to zero. Because R^2 coefficients of determination are not available for treatment models, model performance is also evaluated using two other criteria: the Akaike and Bayesian information criteria (Guo and Fraser, 2010). These diagnostic statistics are measures of combined fit and complexity.

Model specification tests are carried out in two ways. Variables appearing in the models are consistent across PA technology to aid in interpretation of the sign, size, and robustness of coefficients. The variables that appear are selected for model fit, parameter parsimony, and consistency with theory of both innovation adoption and cost and profit function specification. Several other characteristics of the models are tested with created variables. The models estimate the treatment of each PA technology independently, so interaction variables between nonincluded PA technologies (PA options not instrumented with fitted values from the adoption section) are tested in the financial section of the model and are not significant. Interactions are also tested between each significant financial variable and each stewardship measure, and between

Table 7. Impacts of Precision Technologies on Farm Operating Costs and Profit

	GPS Soil/Yield Mapping	Guidance System	VRT
	Percentage Change in Costs/Profits from Adopting		
Operating cost impact of precision technology from treatment model	0.71	1.16	1.81
Operating profit impact	1.10	1.25	1.82

Note: Average treatment effect estimates (on the treated) corrected for correlation between adoption and profit/cost sections of each treatment model (Tables 3 and 4). GPS, Global Positioning System; VRT, variable rate input application technology.
Source: USDA, Economic Research Service estimates using data from the Agricultural Resource Management Survey Phase II and Phase III.

nonincluded PA technologies and each significant stewardship measure. None of the 50 tested interaction variables are significant, giving some confidence that omitted variables do create endogeneity issues. The PA technologies themselves are fully instrumented in the adoption section of each model.

As a formal test of this no-omitted variables conclusion; individual observations that fall into treatment (adopters) and nontreatment groups are separated and a $\chi^2(1)$ test of overidentification of the balance between the sets of covariants in the groups is used. All six estimated models pass this overidentification test at the 90% level or higher. Five equations pass at the 99% level, and test statistics are shown in Table 6.

The last group of results (Table 7) shows the average operating costs and profits treatment effect of PA on the treated (PA adopters). For farms that use the technology compared with those that do not, VRT has the largest average effect on both operating costs and profit in soybean production, holding input costs and stewardship practices constant. The difference between the cost effect and the profit effect, however, is the smallest of the three PA technologies. VRT appears to be the most costly to implement as might be expected; however, the increase in associated profit covers the additional capital costs, but only narrowly on average. Some farmers would presumably not benefit from enough of a yield increase to cover their additional costs.

For farms that use the technology compared with those that do not, GPS mapping shows the smallest cost increase and the largest yield and profit increase above additional costs, probably because of lower costs of implementation that rely more on computer know-how than on capital equipment. For farms that use the technology compared with those that do not, guidance systems lie between these two extremes with increases in both costs and profit, but not as large an increase in profit over costs as for GPS mapping. This would be consistent with the difficulty measuring convenience and stress reduction that has been associated with guidance and might be counted as a benefit by the farmer. Even with these limitations, the guidance treatment-effect estimate in the table is close to the 0.9% profit impact estimated by Shockley, Dillon, and Stombaugh (2011). These estimates are overall impacts of PA technology adoption on farms that use the technology compared with those that do not, which takes into account all the factors related to overhead, input costs, and stewardship practices in Tables 4 and 5.

6. Conclusions

PA would be expected to affect row-crop production costs and profits through intensified site-specific management of production information. If the information is too costly to obtain, and the benefits in increased yield and profit are too small in specific circumstances, information-intensive production may not be adopted. The objective of this article was to consider if crop production ecosystem stewardship making use of BMPs in soybean production benefits from PA's information technologies on farms that use PA compared with those that do not. The recent embrace of certain precision technologies on medium to large soybean farms begs the question, how does intensified information management affect aggregate stewardship in soybean production?

Using existing standards and protocols, stewardship is investigated through the use of BMPs. Treatment-effects model empirical estimates show that soybean crop production stewardship BMPs can benefit from PA information technologies to varying degrees. Separate estimates are developed for operating costs and profits because BMPs can be affected differently by farmers' efforts to lower costs or increase yields and profit. These empirical estimates are for only 1 year and are unable to discern if individual producers were low-cost or high-profit producers before they adopted PA. After accounting for the fact that PA adoption does usually affect overhead expenditures, four sustainable production BMPs add more to average profit than costs. These BMPs are field operation adjustments to reduce fertilizer use, extensive nutrient tests, scouting for weeds by consultants, and crop rotation. Conservation tillage reduces costs, and erosion control lowers operating profit.

Taken together, these results indicate that information from PA can promote stewardship and increase profits, but in some cases, it may raise operating costs. It is possible that farmers interested in intensifying management to improve profits seek out both PA and sustainable management. Another possible explanation would be that PA information and the precision application capacity of PA technology make it easier to adopt the sustainable practices. The size of the estimated impacts in the current framework are modest, but the question answered is whether stewardship practices are positively associated with PA. The actual size of the ecological benefit that includes the value of ecosystem services is left for future work.

Evidence of a connection between PA and stewardship goals could affect agricultural crop production research. Work in this area often requires interdisciplinary collaboration to address trade-offs in competing production systems. A baseline framework for research was issued by the National Research Council of the National Academy of Sciences that envisioned an agricultural system than could produce an adequate supply of food, fiber, and animal feed without harming the natural environment or hampering responses to climate change, while providing positive impacts on local communities, farm labor, and animal welfare (National Research Council, 2010). Researchers may need to consider precision technologies when studying how to help farmers meet those goals.

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