An Economic Assessment of the Whole-farm Impact of Precision Agriculture

Kent Olson and Pascal Elisabeth

Applied Economics Department
University of Minnesota
St. Paul, Minnesota 55108

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ABSTRACT

The full impact of an investment in a management information system (MIS), such as precision agriculture (PA), comes from improved managerial decision making throughout the whole farm and not just from improvements in a specific part of the farm. This study was conducted to determine whether the adoption of PA had a positive impact on whole-farm profitability. To overcome problems of simultaneity and self-selection in the adoption decision of PA, this study used a two stage econometric model using data from farms in Southwest Minnesota. The PA adoption decision was evaluated in the first stage, and the impact of adopting PA was evaluated in the second stage. The whole farm rate of return to assets (ROA) was used to measure the impact of PA. For all 212 farms in the dataset, the adoption of precision agriculture was explained significantly ($p<0.1$) by two variables: positively by the farmer's self-described soil variability and negatively by the level of non-farm income. For the 63 crop farms in the dataset, adoption of PA was explained significantly ($p<0.1$) only by the farmer's self-described soil variability. The adoption of PA was estimated to have a significant ($p<0.1$) negative impact on ROA for the entire group of farms but was not significant when the farms were separated into crop farms only and into size clusters. PA's lack of significance in explaining ROA in the subgroups may be due to small sample size, the variability of ROA itself, the lack of fully implementing PA as an MIS, differences in management ability, and the availability of other farming methods that are just as profitable as PA.

Keywords: precision agriculture, economics, adoption, profitability

INTRODUCTION

Although it involves mechanical technology, precision agriculture (PA) or site specific resource management is, more precisely, a management information system (MIS). Traditional benefit-cost and investment analyses do not capture the full impact of a specific investment in information technology if it is analyzed as an isolated investment since the profitability of an improved and fully implemented MIS comes from improved managerial decision making for the whole farm not just as improvements in easily seen efficiencies (Hamilton and Chervany 1981, Lincoln and Shorrock 1990, Kleijnen 1980, Parker et al. 1988; Banker and Kauffman 1989). This study builds on the work by Tomaszewski et al. (2000), Verstegen (1998), Zacharias, Huh, and Brandon (1990), Lowenberg-DeBoer and Swinton (1995) and others to develop an analytical framework for estimating PA's impact on whole-farm profitability. Data from the Southwestern Minnesota Farm Business Management Association (e.g., Olson et al., 2001) are used to assess the impact on the whole farm rate of return to assets (ROA) of differences in the level of PA use, farm size and location, crop yield, soil characteristics, operator age and education, and so on. By using ROA, we will be able to see the impact of not only improving input efficiency (e.g., better fertilizer recommendations), improving resources (e.g., adding drainage), etc., we will also be able to see the impact in how decisions are made, more attention paid to hard data versus hunches, changes away from traditional methods, etc. Following Fernandez-Cornejo & McBride (2000), we use a two stage model to estimate the impact of adopting precision agriculture and to account for simultaneity and self-selection in the adoption decision. The first stage is the adoption decision model and the second stage is the impact model (of using precision agriculture).

DATA COLLECTION AND ANALYSIS METHODS

In January 2001, during their year-end analysis for 2000, the 212 farmer-members in the Southwestern Minnesota Farm Business Management Association were surveyed regarding their use of precision agricultural techniques. In two separate studies, the farmers who belong to a management association were found to be larger than the average farm reported by the agricultural census and were more likely to have livestock (Andersson and Olson, 1996; Tvedt, Olson, and Hawkins, 1989). Each farmer was asked whether they used any of the following techniques considered to be part of what is called precision agriculture:

- Computer generated soil maps
- GPS used to map field boundaries
- GPS used to map problem areas
- GPS assisted soil fertility sampling
- Yield monitor (but no GPS and GIS)
- Yield monitor with GPS
- Yield monitor with GPS and GIS to generate yield maps
- Grid sampling for soil testing
- GPS assisted variable rate fertilizer applications
- GPS assisted variable rate planting
- Profit maps

Multiple layer map analysis

Of the 212 farms surveyed, 59 said they used at least one of the techniques listed above. To analyze the financial impact of adopting precision agriculture, their responses were connected with the information regarding their financial condition and performance collected as part of their year-end analysis.

The decision to adopt site-specific management is not randomly taken by the farm manager. This decision may be related to the size of the farm, to the age of the operator or to the geographical location of the farm. By the same token, the value of the rate of return of the farm assets may be also explained by the age of the operator or the size of the farm. That is, some determinants of the adoption of precision agriculture can also be explaining the level of the rate of return of the farm assets. Then sample selection bias arises. Moreover, some unobserved variables explaining the decision to adopt precision agriculture could be correlated to unobserved explanatory variables of the level of the rate of return, which creates another relationship between the decision to adopt PA and the rate of return. If the unobservables are correlated to the observables then the absence of the unobservables leads to erroneous estimates of the characteristics of the rate of return due to sample selection bias (Vella).

Sample selection models are composed of two equations. The first equation is the equation of interest and the second equation is the "selection rule" that determines when the data in the first equation are observed. A sample selection model has the form:

(1) $y_i = x_i'\beta + \varepsilon_i$; $i = 1, \ldots, N$ and $\varepsilon_i \sim N[0, \sigma_\varepsilon^2]$

(2) $z_i^* = w_i'\gamma + u_i$; $i = 1, \ldots, N$ and $u_i \sim N[0,1]$

(3) $z_i = 1$ *if* $z_i^* > 0$ (farm adopts PA)

(4) $z_i = 0$ *if* $z_i^* \le 0$ (farm doesn't adopt PA)

Equation (2) is the selection equation, where z_i^* is unobserved and z_i is observed. The variable of interest y_i (rate of return) is observed only when $z_i^* > 0$, that is the farm's manager used precision agriculture. β and γ are the vectors of unknowns parameters and ε_i and u_i are the errors terms with $E[\varepsilon_i \mid u_i] \neq 0$.

The expected value of y_i conditional on y_i being observed is $E[y_i / z_i = 1] = E[y_i \mid u_i > -w_i'\gamma] = x_i'\beta + E[\varepsilon_i \mid u_i > -w_i'\gamma]$. There exist two main parametric methods used to estimate the selection model that depend on the assumption that ε_i and u_i are independently and identically distributed and (ε_i, u_i) are independent of w. The first method described by Heckman (1974) is to compute a maximum likelihood estimator. This method is too tedious and relies heavily on normality assumptions regarding ε_i and u_i. The second method was proposed also by Heckman (1976, 1979). His strategy overcomes the misspecification of the conditional mean of y when Equation (1) is estimated using OLS (since $E[\varepsilon_i \mid u_i > -w_i'\gamma] \neq 0$) by adding a correction term to explain $E[\varepsilon_i \mid u_i > -w_i'\gamma]$. Heckman rewrote the expectation as

$E[\varepsilon_i \mid u_i > -w_i'\gamma] = \rho\sigma_\varepsilon\lambda(-w_i'\gamma)$

where $\lambda\left(-w_i'\gamma\right)=\phi\left(w_i'\gamma\right)/\Phi\left(w_i'\gamma\right)$, with $\phi(\cdot)$ being the probability density function of the standard normal distribution and $\Phi(\cdot)$ being the cumulative distribution function of the standard normal distribution and ρ being the correlation coefficient between *y* and *z*. The ratio of the function denoted $\lambda(\cdot)$ is called the inverse Mills ratio. Equation (1) becomes

$$\left(y_i \mid z_i = 1\right) = \beta' x_i + \rho\sigma_\varepsilon \lambda_i + v_i$$

Heckman proceeds in two steps. First he runs a probit on Equation (2) to estimate the inverse Mills ratio and obtains $\hat{\lambda}=\phi\left(w_i'\hat{\gamma}\right)/\Phi\left(w_i'\hat{\gamma}\right)$ and $\hat{\delta}_i=\hat{\lambda}_i\left(\hat{\lambda}_i-w_i'\hat{\gamma}\right)$. In a second step, he regresses *y* on *x* and $\hat{\lambda}$ using OLS to obtain β and β_λ. The coefficient on $\hat{\lambda}$ is an estimate of $\rho\sigma_\varepsilon$.

This application of the OLS in the second stage gives consistent estimates of β, but the estimates of the covariance of β are incorrect. There are two reasons for that (Greene). First, v_i is heteroscedastic,

$$\operatorname{var}\left[v_i\right]=\sigma_\varepsilon^2\left(1-\rho^2\delta_i\right).$$

And second, $\hat{\gamma}$ is just an estimate of γ, since there are unknown parameters in λ_i. The correct form for the estimates of the covariance of β*'s* (which include β and β_λ) is $Var\left[b,b_\lambda\right]=\hat{\sigma}_\varepsilon^2\left[X'X\right]^{-1}\left[X'\left(I-\hat{\rho}^2\hat{\Delta}\right)X+Q\right]\left[X'X\right]^{-1}$

where $\hat{\sigma}_\varepsilon=\frac{1}{n}\sum_{i=1}^{n}\left(y_i-x'b\right)^2+\frac{1}{n}\sum_{i=1}^{n}\hat{\lambda}_i\left(\hat{\lambda}_i+w_i'\hat{\gamma}\right)b_\lambda^2$; $\hat{\rho}^2=b_\lambda^2/\sigma_\varepsilon^2$; $\left(I-\hat{\rho}^2\hat{\Delta}\right)$ is an *nxn* diagonal matrix with $1-\hat{\rho}^2\hat{\lambda}_i\left(\hat{\lambda}_i+w_i'\hat{\gamma}\right)$ the *i*th diagonal element;

and $Q=\hat{\rho}^2\left(X'\hat{\Delta}W\right)Var(\hat{\gamma})\left(X'\hat{\Delta}W\right)$ with $Var(\hat{\gamma})$ being the covariance matrix from the probit estimate.

Though there exist more discussions about sample selection models (particularly semi-parametric methods), we limit our analysis to Heckman's two-step model with the corrected form for the estimates of the covariance of β*'s*.

RESULTS

The average ROA was 13.0% for all 212 farms and 13.6% for the 59 farms who said they were using PA (Table 1). The 63 crop farms (operations in which crop income constitutes 70% or more of the total gross income for the farm) had an average ROA of 10.5% and the 16 crop farms who said they were using PA had an average ROA of 10.2%.

The farms using PA tended to be larger on average by several measures. The average farm had 730 acres of crops; the average farm using PA had 845 crop acres. PA farms had a higher average gross income and higher asset values than all farms.

Farmers using PA gave their fields a higher variability index; 3.2 compared to 1.3 for all farms.

These data were used to estimate the significance of variables in explaining adoption of PA and, as described earlier, to estimate the impact of adopting PA on the financial performance of the farms

For all 212 farms in the dataset, the adoption of precision agriculture was explained significantly ($p<0.1$) by two variables: positively by the farmer's self-

Table 1. Descriptive statistics of farms in survey.

Variable	All 212 farms	59 PA farms	63 crop farms	16 PA crop farms
Rate of Return on Assets (%, ROA, cost basis)	13.0 (10.6)[1]	13.6 (11.0)	10.5 (11.9)	10.2 (12.3)
Crop acres	730 (489)	845 (519)	714 (439)	864 (583)
Owned acres	214 (256)	245 (274)	214 (228)	259 (363)
Gross income ($)	422,897 (466,918)	480,880 (365,175)	260,107 (159,097)	310,593 (192,001)
Crop share of gross income (%)	51.0 (25.5)	48.6 (23.9)	78.1 (6.2)	77.0 (5.2)
Average Farm Asset Value ($, cost basis)	693,642 (597,562)	811,718 (547,021)	490,772 (374,590)	603,655 (585,515)
Average Farm Asset Value ($, market value)	1,042,603 (860,413)	1,215,130 (837,501)	765,917 (566,459)	899,681 (902,402)
Total % in Debt (cost basis)	52.1 (20.8)	53.1 (19.2)	49.9 (19.5)	49.8 (18.5)
Net non-farm income ($)	21,436 (25,351)	15,045 (15,784)	29,570 (26,414)	24,619 (15,852)
Age of main operator (years)	47.4 (10.7)	47.9 (11.8)	48.1 (10.9)	46.4 (12.2)
Years farming, main operator	24.2 (11.1)	25.3 (11.5)	23.5 (11.9)	23.8 (12.6)
Variability[2]	1.3 (1.8)	3.2 (1.3)	1.3 (1.9)	3.3 (1.7)

[1]Standard deviation in parentheses.
[2]Variability is the farmer's self-described index of the variability of their fields based on soil type, slope, wetness, and so on. It ranges from 1 to 5 with 5 indicating most variable.

described soil variability and negatively by the level of non-farm income (Table 2). The county the farm was situated in, the age of the main operator, the size of the farm as measured by the number of crop acres, and the level of debt were not significant in explaining PA adoption. The estimated Probit model predicted 83.5% of the farms correctly as to whether they adopted PA or not.

Table 2. Estimated Probit model for the probability of adopting precision agriculture using all 212 farms.

Variables	Estimates	t statistic
Constant	-1.27	-1.44
VARIABILITY[1]	0.65	8.17*
COUNTY	-0.13E-02	-0.37
AGE	-0.79E-02	-0.61
CROP ACRES	0.75E-04	0.28
DEBT	0.51E-02	0.78
NONFARM	-0.17E-04	-2.60*
Chi-squared	110.35	
% predicted correctly	83.5%	

*Significant at $p<0.1$

[1]Variables defined in Table 3.

Table 3. Definition of the variables.

Variables	Definitions
VARIABILITY	The farmer's self-described index of the variability of their fields based on soil type, slope, wetness, and so on. The index ranges from 1 to 5 with 5 indicating most variable.
COUNTY	County of farm operation
AGE	Age of main operator
CROP_ACRES	Number of acres cropped (owned plus rented)
DEBT	Average dollar amount of debt held by farm
YEARS_FARMING	Number of years the main operator has been farming
LABOR_HOURS	Number of hours worked per year, self-estimated
GROSS_INCOME	Total gross income for farm (dollars)
OPERATING_EXPENSES	Total operating expenses for farm (dollars)
COST_ASSET	Average value of all farm assets (cost basis)
GOVT_INCOME	Total of income from all government sources and programs
NONFARM_INCOME	Total net income from nonfarm sources
PA	Binary variable, 1 if farm adopted PA, 0 if not
PA-HAT	Estimated probability of adopting precision agriculture
LAMBDA	Estimate of the inverse Mills ratio

The adoption of PA was estimated to have a significant ($p<0.1$) negative impact on ROA for the entire group of farms (Table 4). This impact was estimated to be –10% on ROA. Others variables that had a significant ($p<0.1$) effect on ROA were labor hours (negative), gross income (positive), operating expenses (negative), asset level (negative), government income (positive), and non-farm income (negative).

Since the types of farms in the entire dataset were very diverse, the next step was to select only those farms on which crop income constituted 70% or more of the total gross income for the farm. Of the total 212 farms, 63 farms were thus classified as crop farms.

For these 63 crop farms, adoption of PA was explained significantly ($p<0.1$) only by the farmer's self-described soil variability (Table 5). For the crop farms, the adoption of PA did not have a significant ($p>0.1$) impact on (Table 6). Others variables that had a significant ($p<0.1$) effect on the crop farms' ROA were the county of residence (negative), years farming (positive), labor hours (negative), gross income (positive), operating expenses (negative), asset level (negative), and non-farm income (negative).

The dataset was also divided into 3 size clusters by using cluster analysis on three variables: crop acreage, crop income, and asset value. The smallest size cluster consisted of 179 farms centered around a crop acreage of 567 acres; crop income of $163,442; and an asset value of $304,196 with assets valued on a cost basis.

For the 179 farms in the smallest size cluster, adoption of PA was explained significantly ($p<0.1$) positively by the farmer's self-described soil variability and negatively by the level of non-farm income (Table 7). For these farms, the adoption of PA did not have a significant ($p>0.1$) impact on (Table 8). Others variables that had a significant ($p<0.1$) effect on the crop farms' ROA were the gross income (positive), operating expenses (negative), asset level (negative), government income (positive), and non-farm income (negative). The other 2 size clusters showed very similar results and are not reported here.

Table 4. Estimated regression coefficients explaining rate of return on assets using all 212 farms.

Variables	Estimates	t statistic
Constant	22.08	3.00*
COUNTY	0.25E-01	0.83
YEARS FARMING	-0.17E-01	-0.17
LABOR HOURS	-0.12E-02	-2.25*
GROSS INCOME	0.86E-04	3.87*
OPERATING EXPENSES	-0.71E-04	-3.47*
COST ASSETS	-0.16E-04	-4.55*
GOVT INCOME	0.10E-03	2.86*
NONFARM INCOME	-0.21E-03	-2.50*
PAHAT	-10.07	-2.77*
LAMBDA	-3.06	-0.81
Adjusted R^2	0.39	
F-Statistic	4.65	

*Significant at $p<0.1$

Table 5. Estimated Probit model for the probability of adopting precision agriculture using the 63 crop farms.

Variables	Estimates	t statistic
Constant	0.35	0.23
VARIABILITY	0.57	4.17*
COUNTY	-0.81E-02	-1.42
AGE	-0.33E-01	-1.24
CROP ACRES	0.49E-03	0.92
DEBT	0.21E-02	0.16
NONFARM INCOME	-0.10E-04	-1.0
Chi-squared	29.85	
% predicted correctly	84.1%	
*Significant at p<0.1		

Table 6. Estimated regression coefficients explaining rate of return on assets using the 63 crop farms.

Variables	Estimates	t statistic
Constant	55.71	2.02*
COUNTY	-0.28	-3.28*
YEARS FARMING	0.64	2.75*
LABOR HOURS	-0.16E-01	-3.26*
GROSS INCOME	0.21E-03	1.97*
OPERATING EXPENSES	-0.17E-03	-2.08*
COST ASSETS	-0.26E-04	-2.54*
GOVT INCOME	0.21E-03	1.23
NONFARM INCOME	-0.87E-03	-2.25*
PA HAT	-6.32	-0.68
LAMBDA	10.62	1.20
Adjusted R^2	0.13	
F-Statistic	1.22	
*Significant at p<0.1		

Table 7. Estimated Probit model for the probability of adopting precision agriculture using the 179 farms in the smallest size cluster.

Variables	Estimates	t statistic
Constant	0.17	0.97
VARIABILITY	0.16	10.77*
COUNTY	-0.16E-03	-0.21
AGE	-0.19E-02	-0.73
CROP ACRES	-0.23E-04	-0.31
DEBT	0.67E-03	0.52
NONFARM INCOME	-0.20E-05	-1.98*
Adjusted R^2	0.42	
% predicted correctly	82.1%	
*Significant at p<0.1		

Table 8. Estimated regression coefficients explaining rate of return on assets using the 179 farms in the smallest size cluster.

Variables	Estimates	t statistic
Constant	18.04	1.81*
COUNTY	0.03	0.77
YEARS FARMING	0.71E-02	0.06
LABOR HOURS	-0.11E-02	-0.67
GROSS INCOME	0.71E-04	2.17*
OPERATING EXPENSES	-0.67E-04	-2.27*
COST ASSETS	-0.18E-04	-2.49*
GOVT INCOME	0.12E-03	2.87*
NONFARM INCOME	-0.28E-03	-2.64*
PA HAT	-3.28	-0.75
LAMBDA	1.44	0.31
Adjusted R^2	0.25	
F-Statistic	2.56	

*Significant at p<0.1

DISCUSSION

While other studies of specific investments in PA have shown positive impacts on the financial performance of farms, similar results were not found by analyzing the performance of a group of farms in Southwestern Minnesota. The significant (p<0.1) but negative effect of PA over all farms in the dataset and PA's lack of significance in explaining ROA in the subgroups may be due to several factors. First, the overall sample of cross-sectional data from 212 farms collected in one year may be too small to capture small impacts of PA compared to the larger impact captured in other variables. In addition, the variability of ROA itself as seen in the descriptive statistics may have created additional difficulty in finding the impact. The lack of fully implementing PA as an MIS also may not have allowed the full benefits to be discovered by the farmers themselves. This lack of a full implementation may be due to PA being a relatively new technology and thus not learned by farmers yet and also due to the complexities of farming and the fact of management attention being drawn to other parts and aspects of the farm business. Another reason may be due to differences in inherent management ability that are not captured in the dataset. Also, the lack of a positive significant impact of adopting PA may be primarily due to the availability of other methods and technologies that are just as profitable as PA. Without a dataset that would have this information, we may not be able to separate the impact of one technology; that is, the impact of only one is lost in the variation of the data.

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