Stochastic Technology, Risk Preferences and Adoption of Site-specific Technologies

Murat Isik and Madhu Khanna

May 15, 2002

Submitted for Presentation as a Selected Paper at the Annual Meeting of American Agricultural Economics Association, July 28-31, 2002, Long Beach, California.

Murat Isik is Associate Scientist at the Center for Agricultural and Rural Development, Iowa State University, 571 Heady Hall, Ames, IA 50011, Tel: (515) 294-0470, E-mail: misik@card.iastate.edu.
Madhu Khanna is Associate Professor at the Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, 326 Mumford Hall, 1301 W. Gregory Dr., Urbana, IL 61801, Tel: (217) 333-5716, E-mail: khanna1@uiuc.edu.

Stochastic Technology, Risk Preferences and Adoption of Site-specific Technologies

Abstract

This paper develops a model of farmer decision-making to examine the extent to which uncertainties about the performance of site-specific technologies (SSTs) and about the weather impact the value of these technologies. The model uses the jointly estimated risk and technology parameters to examine the impacts of SSTs on returns and nitrogen pollution. The availability of uncertain soil information and production uncertainty can lead risk-averse farmers to apply more fertilizers and generate more pollution. Ignoring the impact of uncertainty and risk preferences of farmers leads to a significant overestimation of the economic and environmental benefits of SSTs and underestimation of the required subsidy for inducing adoption of SSTs. The model that accounts for uncertainties about soil conditions and production as well as risk preferences of farmers provides an explanation for the low observed adoption rates of SSTs. Improvements in the accuracy of SSTs have the potential to increase the incentives for adoption.

***Key words*:** spatial variability, risk preferences, joint estimation, uncertainty, technology adoption, nitrogen runoff.

Conventional whole-field management practices apply fertilizers at a single rate uniformly across an entire field. These practices can lead to over-application of fertilizers on some parts of the field and under-application on other parts of the field because soil conditions tend to vary within the field. This can result in lower crop yields than potentially possible in under-supplied areas of the field and wasted inputs and nutrient runoff from the over-supplied areas of the field. Growing concerns about water quality degradation caused by nutrient runoff from fields have led to an interest in finding improved nutrient management techniques that farmers would be willing to adopt voluntarily (or be induced to adopt through cost-share subsidies). Site-specific technologies (SSTs) have generated interest as an improved management technique with the potential to provide both environmental benefits and economic benefits to farmers. SSTs gather detailed information about the soil conditions at a sub-field level, such as nutrient content and potential yields, and utilize that to precisely determine fertilizer application rates that vary across the field to match the spatial variability in the soil conditions. SSTs include grid-based soil sampling, yield monitors that provide yield maps for the field and computerized variable rate fertilizer spreaders.

Several studies have shown the potential for SSTs to reduce input use, increase crop yields and reduce residues of polluting inputs in soils relative to conventional management practices (Thrikawala et al.; Khanna, Isik and Winter-Nelson). Many studies have also evaluated the profitability of SSTs for corn production (see surveys by Lambert and Lowenberg-DeBoer; Swinton and Lowenberg-DeBoer). These studies show that the profitability of SSTs depends on the extent of spatial variability of the soil conditions (Babcock and Pautsch; Schnitkey, Hopkins, and Tweeten; Khanna, Isik and Winter-Nelson), the size of the field (Thrikawala et al.), the extent of rainfall (English, Mahajanashetti, and Roberts; Fixen and Reetz) and uncertainty about output prices (Khanna, Isik and Winter-Nelson). These results are based on the assumption that adoption of SSTs leads to complete certainty about soil conditions and fertilizer needs of the soil. They also assume that yields are deterministic and farmers are risk-neutral.

However, there continues to be considerable uncertainty about the capability of SSTs to accurately measure nutrient content of soils and yields. Yield monitor and soil testing measurements are often subject to technical difficulties and errors, which can lead to errors in maps of potential yield and soil nutrient content of the field (Searcy et al.; Lowenberg-DeBoer and Hallman; Babcock, Carriquiry and Stern). Farmers also face other sources of uncertainty such as production (yield) uncertainty due to weather that has been shown to influence input application decisions by risk-neutral farmers (Babcock; Babcock and Shogren; Just and Pope) and risk-averse farmers (Ramaswami; Pope and Kramer; Isik). Annual variations in rainfall and temperature can lead to variations in yield of 20% above or below the potential for the same field (Bullock and Bullock) and the impact of the weather varies across different parts of the field. Uncertainty about production and soil conditions may offset the gains achieved from more precise application of inputs and thus the benefits of SSTs. These uncertainties are likely to increase the variability of returns with SSTs more than those with conventional practices that are based on average conditions in the field. This could reduce incentives for switching to SSTs by risk-averse farmers.

The purpose of this paper is to develop a framework of farmer decision-making to analyze the impacts of risk preferences and uncertainties about weather and soil conditions on adoption of SSTs. The paper also analyzes the implications of adoption of SSTs for the potential they offer for reducing nitrogen pollution under uncertainty and risk aversion. To the extent that uncertainty and risk-aversion create disincentives for adoption of SSTs and for reducing nitrogen use, adoption of SSTs may be induced by providing subsidies, through programs such as the Environmental Quality Incentives Program. This paper examines the implications of uncertainty and risk-aversion for the design of cost-share subsidies to induce adoption of SSTs. We implement this framework by first estimating the stochastic technology and risk preference parameters jointly, using survey data from farmers in OtterLake Watershed in Illinois. These risk and technology parameters are then incorporated into a micro-level utility maximization model to simulate the impacts of risk aversion and uncertainty on adoption decisions and to analyze their implications for the cost-share subsidies needed to induce adoption.

There is a large theoretical literature showing that risk aversion, in the presence of various types of uncertainties, can influence input use (Ramaswami; Pope and Kramer; Leathers and Quiggin; Karagiannis; Isik) and technology adoption decisions (Feder; Robison and Barry; Just and Zilberman). These studies have used whole-field analysis, assuming that there is no variability in nutrient content and soil quality within the field. The empirical literature analyzing the impact of uncertainty and risk aversion on production decisions has also been based on whole-field analysis only and has either estimated stochastic production functions without estimating utility function parameters and used those in a simulation to examine the impact of risk on input use (Dai, Fletcher, and Lee; Lambert) or estimated the coefficients of risk aversion (Bar-shira, Just and Zilberman). Joint estimation of stochastic technology and risk preferences has been done by a few studies only (Love and Buccola; Saha, Shumway and Talpaz; Saha; Bontems and Thomas) and is preferred because it leads to gains in efficiency of estimation of risk and technology parameters. Most of these studies have however, imposed restrictive assumptions on the utility function. Love and Buccola used an exponential utility function that imposes constant absolute risk aversion. Bontems and Thomas used a power utility function that imposes constant relative risk aversion. Saha, Shumway and Talpaz proposed the use of a more flexible utility function that does not restrict risk preferences. Although this method does not impose any restriction on producers' risk preference, it is difficult to obtain tractable results with a larger input set or more flexible functional forms since it requires numerical integration over the production error term (Saha). We, therefore, use the nonlinear mean standard deviation utility function, proposed by Saha, which does not put any restriction on risk preferences and does not require numerical integration while jointly estimating the risk and technology parameters. With the exception of Bontems and Thomas, none of these studies have used these jointly estimated parameters in a simulation model to examine their implications for input use and/or technology adoption decisions. Bontems and Thomas consider a model of sequential nitrogen application under risk to compute the value of information about nitrogen availability in the soil and risk premium in corn production assuming constant relative risk aversion. In this paper, we estimate the risk preferences and technology parameters without imposing restrictive assumptions on the utility function. We also analyze the extent to which the impact of risk aversion and uncertainty varies across heterogeneous farmers.

While SSTs are making it possible for farmers to do variable rate input applications within the field, the gains in expected profits due to adoption of SSTs depend on spatial variability of the soil conditions within the field as well as uncertainties about the performance of the technology and about weather. This paper shows how spatial variability in the field can mitigate the extent to which risk aversion and uncertainty can influence adoption of SSTs. Ignoring the impact of uncertainty and risk preferences of farmers could lead to overestimation of economic and environmental benefits of SSTs and underestimation of the required subsidies to induce adoption of SSTs.

Theoretical Model

Consider a farmer with a fixed land holding *A*. Suppose that the land can be divided into *M* homogeneous sites of size A_i such that $\sum_{i \in M} A_i = A$. The farmer has a choice of two technologies, conventional practices and SSTs, represented by superscripts *C* and *S*, respectively. The constant returns to scale production function is represented by $y_i = f(x_i, z_i) + u_i$, where x_i is the applied input per acre, z_i is the level of soil attribute (nutrient content) per acre at site *i*, y_i is yield per acre, and u_i is a random error term with mean zero and $Var(u_i) = \exp(\beta x_i)$. This variance specification, introduced by Harvey and used by Asche and Tveteras, ensures positive output variance that is a function of the fertilizers applied. It represents the effect of uncertainty due to the weather, which affects production using both conventional practices and SSTs. An input is said to be risk increasing (decreasing) if $\beta > (<) 0$ under uncertainty about weather. It is assumed that $f_x > 0$, $f_z > 0$, and $f_{xx} < 0$. The sign of f_{xz} can be negative or positive depending on whether the applied input and the soil attribute are substitutes or complements. If *z* represents soil fertility, such as soil nitrate level, it is a substitute for applied nitrogen and f_{xz} is negative because an increase in soil nutrient level results in a decrease in the marginal product of input *x*. On the other hand, if *z* represents organic matter in the soil (which determines the quality of the soil and its potential crop yields), f_{xz} could be positive, since higher quality soils allow plants to use nitrogen more effectively and increase the marginal product of nitrogen. It is assumed that z_i varies within the field with mean $\bar{z}$ and variance δ^2. The input price *w* and output price *P* are assumed that known with certainty.

With conventional practices, the farmer lacks information about the distribution of the soil attribute within the field and uses a representative sample of soil tests to estimate the average soil attribute level in the field. The farmer then chooses a single rate of input application per acre, x^C, for the whole field given the average soil attribute level. This approach to determining the input application rate is also referred to as the averaging approach (Khanna, Isik and Winter-Nelson; Babcock and Pautch). In the presence of uncertainty about the average soil attribute level, the farmer considers the production function to be represented by $y_i = f(x_i, \bar{z}, \bar{z}\varepsilon^C) + u_i$, where ε^C is a random variable with mean zero and variance $\left(\sigma_\varepsilon^C\right)^2$.

Adoption of SSTs imposes a fixed cost of K to undertake detailed soil testing and investment in variable rate technologies. This enables the application of the input at a varying rate, x_i, at each site in the field given the measured level of the soil attribute at that site. However, even adoption of SSTs cannot provide complete and accurate information about soil conditions. With SSTs the production function is represented by: $y_i = f(x_i, z_i, z_i\varepsilon^S) + u_i$, where ε^S is a random variable with mean zero and variance $\left(\sigma_\varepsilon^S\right)^2$ that varies proportionally with the level of the soil attribute. The first-order approximation of this function is $y_i = f(x_i, z_i) + f_z(x_i, z_i)z_i\varepsilon^S + u_i$, which is similar to the Just-Pope production function, $y = f(x,z) + h(x)u$. In the case of the Just-Pope specification, the risk increasing (decreasing) effect of an input is represented by $h_x > (<) 0$ and represents the effect of production uncertainty. In this paper, the risk increasing (decreasing) effect of an input under uncertainty about soil conditions is represented by $f_{xz} > (<) 0$ and depends on whether x and z are substitutes or complements.

Decision Problem under Uncertainty

We model the farmer's decision to adopt SSTs using a procedure proposed by Meyer. The decision criterion, $U(\pi, \sigma)$ assumes that an agent's optimal choice is made by ranking alternatives through a preference function defined over the first-two moments of the random payoff, mean π and standard deviation σ with $U_\pi > 0$ and $U_\sigma < 0$. The farmer maximizes:

$$\max_{x,I} U\left(\pi^C + I(\pi^S - \pi^C - K), \sigma^C + I(\sigma^S - \sigma^C)\right) \tag{1}$$

where I is the technology choice (1 for adoption of SSTs, 0 for non-adoption); $\pi^C = \sum_{i\in M} A_i\left(Pf(x^C, \bar{z}) - wx^C\right); \pi^S = \sum_{i\in M} A_i\left(Pf(x_i, z_i) - wx_i\right)$;

$\sigma^C = AP\left(\exp(\beta x^C) + (\sigma_\varepsilon^C \bar{z} f_z(x^C, \bar{z}))^2\right)^{1/2}$; and $\sigma^S = P\left(\sum_{i\in M} A_i\left(\exp(\beta x_i) + (\sigma_\varepsilon^S z_i f_z(z_i, x_i))^2\right)\right)^{1/2}$.

The utility-maximizing adoption decision is obtained by finding the utility-maximizing levels of input use with adoption of SSTs and with conventional practices and then comparing the maximized expected utility with each technology. Assuming an internal solution, $x^C > 0$ and $x_i > 0$, the uniform input application under conventional practices is determined such that $U_\pi\left(\partial\pi^C/\partial x^C\right) + U_\sigma\left(\partial\sigma^C/\partial x^C\right) = 0$, leading to:

$$Pf_x(x^C, \bar{z}) - w - R(\pi^C, \sigma^C)/\sigma^C\, P^2\left(\beta/2\exp(\beta x^C) + (\bar{z}\sigma_\varepsilon^C)^2 f_z(x^C, \bar{z}) f_{xz}(x^C, \bar{z})\right) = 0 \tag{2}$$

where subscripts denote partial derivatives; and $R(\pi^C, \sigma^C) = -U_\sigma/U_\pi > 0$ since $U_\sigma < 0$ represents the risk attitude. Under SSTs, the first-order condition of the maximization problem is used to obtain the input levels at a point in the field as:

$$Pf_x(x_i, z_i) - w - R(\pi^S, \sigma^S)/\sigma^S\, P^2\left(\beta/2\exp(\beta x_i) + (\sigma_\varepsilon^S z_i)^2 f_z(z_i, x_i) f_{xz}(z_i, x_i)\right) = 0\,. \tag{3}$$

The impact of uncertainty and risk aversion on input use arises from the existence of a marginal risk premium, which is the wedge between the input cost and the expected marginal product at the optimal input use (Ramaswami; Pope and Kramer). A risk-averse farmer uses more (less) of an input having a negative (positive) marginal risk premium. The marginal risk premium under SSTs could be greater than that under conventional practices depending on the variability of returns and the magnitude of risk aversion parameters. Even if there were no soil uncertainty, the impact of uncertainty and risk aversion on input use could differ with conventional practices and SSTs because of differences in the magnitude of risk aversion and in the marginal product of *x* at each site relative to that under average soil conditions.

We now examine the impact of soil uncertainty on input use in the field with adoption of SSTs and conventional practices by totally differentiating (2) and (3) to obtain:

$$\frac{dx_i}{d\sigma_\varepsilon^S} = \frac{1}{B^S} R(\pi^S, \sigma^S) P z_i f_{xz} \text{ and } \frac{dx^C}{d\sigma_\varepsilon^C} = \frac{1}{B^C} R(\pi^C, \sigma^C) P \bar{z} f_{xz} \tag{4}$$

where $B < 0$ is the second-order condition. Equation (4) is negative (positive) if the input is risk increasing (decreasing) represented by $f_{xz} > (<) 0$. Thus, an increase in the degree of uncertainty about soil conditions increases (decreases) the use of a risk-decreasing (risk-increasing) input with both conventional and site-specific practices.

Field-Level Impact of Adoption of SSTs on Input Use and Quasi-rents

The first-order conditions in (2) and (3) are used to determine the impact of adoption of SSTs on input use and quasi-rents. To obtain the difference in input use between SSTs and conventional practices, we assume for simplicity that there is no production uncertainty and equate the first-order conditions[1]: $f_x(x_i, z_i) - R^S \sigma_\varepsilon z_i f_{xz}(z_i, x_i) = f_x(x^C, z^C) - R^C \sigma_\varepsilon^C \bar{z} f_{xz}(x^C, \bar{z})$.

Define the elasticity of marginal product with respect to *z* as: $\in_{Mi} = \frac{z_i f_{xz}(x_i, z_i)}{f_x(x_i, z_i)}$ and $\in^C = \frac{\bar{z} f_{xz}(x^C, \bar{z})}{f_x(x^C, \bar{z})}$. Under uncertainty about soil conditions, these elasticities are negative (positive) when the input is risk decreasing (increasing) represented by $f_{xz} < (>) 0$. Use $\in_{Mi}$ and

[1] In the empirical application of the model however, we consider the case where production uncertainty is present both by itself and together with uncertainty about soil conditions.

$\in^C$ to obtain $f_x(x_i, z_i)(1-\phi_i^S) = f_x(x^C, \bar{z})(1-\phi^C)$, where $\phi_i^S = R^S \sigma_\varepsilon^S \in_{Mi} < 1$ and $\phi^C = R^C \sigma_\varepsilon^C \in^C < 1$. By using a first-order Taylor series expansion around $\bar{z}$ and x^C we obtain the difference in input use at site *i* as:

$$x_i - x^C \cong \frac{f_x(\phi_i^S - \phi^C)}{f_{xx}(1-\phi_i^S)} - \frac{f_{xz}(z-\bar{z})}{f_{xx}} - \frac{1}{2}(z-\bar{z})^2 \frac{d^2x}{dz^2} \tag{5}$$

where the derivatives of the production function are evaluated at $\bar{z}$ and x^C; and d^2x/dz^2 is the total second derivative of x with respect to z given by $\frac{d^2x}{dz^2} = \frac{1}{f_{xx}^2}\left[2 f_{xz} f_{xzz} - f_{xx} f_{xzz} - \frac{f_{xz}^2 f_{xxx}}{f_{xx}}\right]$. This is consistent with the results obtained by Katz, and by Hennessy and Babcock. The sign of d^2x/dz^2 depends on the signs of third own- and cross derivatives of the production function and could be positive or negative. Aggregating (5) over all the sites in the field, the per-acre difference in the input use between SSTs and conventional practices is:

$$\Delta x = \frac{1}{A}\sum_{i \in S} A_i\left(x_i^V - x^C\right) = \frac{1}{2}\sigma_Z^2 \frac{d^2x}{dz^2} + \frac{1}{A}\sum_{i \in S} A_i\left(\frac{f_x(\phi_i^S - \phi^C)}{f_{xx}(1-\phi_i^S)}\right). \tag{6}$$

The change in input use with adoption depends on the second and third own and cross derivatives of the production function as well as on the degree of risk aversion and magnitude of uncertainty about soil conditions with conventional practices and SSTs. Its magnitude also depends on the spatial variability in z across the field. The first term in (6) could be positive or negative depending on the sign of d^2x/dz^2. The second term is negative (positive) if $\phi_i^S > \phi^C$ ($\phi_i^S < \phi^C$) for all *i*. Under certainty and risk-neutrality ($R = 0$), the difference in the mean input use is given by $\Delta x = \frac{1}{2}\sigma_Z^2 \frac{d^2x}{dz^2}$. If all the third derivatives of the production function are equal to zero, $d^2x/dz^2 = 0$. In that case, adoption of SSTs does not affect the mean input use, i.e.,

$\Delta x = 0$, as shown by Hennessy and Babcock. However, with risk aversion and uncertainty about soil conditions, adoption of SSTs affects the mean input use even when the third derivatives of the production function are zero. In this case, the difference in mean input use is $\Delta x = \frac{1}{A}\sum_{i \in S} A_i \left(\frac{f_x(\phi_i^S - \phi^C)}{f_{xx}(1-\phi_i^S)} \right)$. The difference in the mean input use could be positive or negative depending on the values of $R^S, \sigma_\varepsilon^S, \in_{Mi}, R^C, \sigma_\varepsilon^C$, and $\in^C$. Note that even with $\sigma_\varepsilon^S < \sigma_\varepsilon^C$, Δx could be positive or negative. This is because R^S could be greater than R^C and $\in^C > \in_{Mi}$ for some *i*, and $\in^C \leq \in_{Mi}$ for others. An increase in σ_ε^S leads to a decrease (increase) in Δx if the input is risk decreasing (increasing). On the other hand, an increase in σ_ε^C increases (decreases) Δx if the input is risk decreasing (increasing).

When there is no uncertainty about soil conditions with adoption of SSTs $(\phi_i^S = 0)$, $\Delta x = - f_x \phi^C / f_{xx}$, indicating that adoption of SSTs reduces (increases) the use of a risk decreasing (increasing) input. However, under risk aversion and uncertainty about soil conditions with SSTs, adoption of SSTs could lead to an increase or decrease in the mean input use even with zero third derivatives of the production function, unlike the case obtained under certainty about SSTs and risk-neutrality by Hennessy and Babcock.

The quasi-rent difference between SSTs and conventional practices is obtained by: (a) taking a second-order Taylor series expansion of the production function around $\bar{z}$ and x^C, (b) plugging (6) into this approximation, and (c) aggregating over all sites. The per-acre difference in the quasi-rents between SSTs and conventional practices is then estimated as:

$$\Delta\pi = \frac{-P}{2 f_{xx}} \left[\delta^2 (f_{xz})^2 - \frac{(f_x)^2}{A} \sum_{i \in S} A_i \left(\frac{(\phi_i^S - \phi^C)^2 + 2(\phi_i^S - \phi^C)\phi^C (1-\phi_i^S)}{(1-\phi_i^S)^2} \right) \right]. \qquad (7)$$

When there is no uncertainty about soil conditions with adoption of SSTs $(\phi_i^S = 0)$, the per-acre quasi-rent differential is $\Delta\pi = \frac{-P}{2f_{xx}}\left[\delta^2\left(f_{xz}\right)^2 + \left(f_x\right)^2(\phi^C)^2\right] > 0$, which is greater than (7). Thus, Adoption of SSTs always leads to an increase in the quasi-rent differential under certainty about soil conditions with SSTs. An increase in the degree of uncertainty about soil conditions with conventional practices (ϕ^C) increases the quasi-rent differential. Note that when there is no uncertainty about soil conditions $\Delta\pi = \frac{-P\delta^2\left(f_{xz}\right)^2}{2f_{xx}}$. The quasi-rent differential increases with an increase in the variability of the soil attribute within the field, an increase in output price, and an increase in the concavity of the production function.

Ceteris paribus**,** an increase in risk aversion and/or degree of uncertainty about soil conditions with SSTs increases the value of ϕ_i^S in (7), thereby decreasing the quasi-rent differential. This impact, however, varies with the nature of input and value of the elasticity of marginal product. Risk aversion and uncertainty about soil conditions have a greater impact on the quasi-rent differential if the input is risk increasing, i.e., $f_{xz} > 0$. The higher the elasticity of marginal product, $\in_{Mi}$, the higher is the absolute value of (ϕ_i^S), and therefore the higher the impact of risk aversion and uncertainty on the quasi-rent differential.

Adoption Decision and Cost-share Subsidy

Using the utility-maximizing input rates, the farmer adopts SSTs if $U\left((\pi^S - K), \sigma^S\right) > U\left(\pi^C, \sigma^C\right)$. Otherwise, the farmer would continue to use conventional practices. The incentives to adopt SSTs are a positive monotonic transformation of the increase in the expected utility with adoption. Expected utility increases with an increase in the returns from adoption and a decrease in the cost of adoption. As shown above, the returns from adoption of SSTs, in turn, increase with an increase in the variability of soil attribute within the field. Incentives to adopt decrease as the variability of returns with SSTs increase, which occurs with an increase in the degree of uncertainty about soil conditions. These results indicate that an improvement in the accuracy of SSTs has the potential to increase the incentives for adoption of SSTs, particularly by risk averse farmers.

A cost-share subsidy may be used to induce adoption of SSTs when it is not otherwise profitable to adopt. When there is no uncertainty about soil conditions with risk neutrality, the required cost-share subsidy to induce adoption of SSTs is the difference between the cost of investment and the returns when the former is greater than the latter, i.e., $K + \frac{P\delta^2 \left(f_{xz}\right)^2}{2 f_{xx}}$. Thus, the incentive payment a farmer needs to induce adoption of the technology depends on field-specific factors such as spatial variability and the characteristics of the production function and economic variables such as output price.

The required subsidy to induce adoption of SSTs under uncertainty about soil conditions and risk aversion is given by: $K - \Delta\pi + U^{-1}\left[U\left((\pi^S - K, \sigma^S\right)\right] - U^{-1}\left[U\left(\pi^C, \sigma^C\right)\right]$. Thus, the required subsidy depends on the magnitude of uncertainty about soil conditions and risk aversion (utility function parameters), and the distribution of soil characteristics within the field. The magnitude of the impact of uncertainty and risk aversion on the returns with adoption of SSTs, adoption decision and required cost-share subsidies to induce adoption of SSTs is an empirical question and we examine that by developing an empirical model applied using data for Illinois.

Empirical Method

To operationalize the framework developed above, we assume the following flexible utility function proposed by Saha:

$$U(\pi,\sigma) = \pi^{\theta} - \sigma^{\gamma} \tag{8}$$

where π and σ are defined above; and $\theta > 0$ and γ are parameters. This function, also called a nonlinear mean standard deviation utility function, provides flexibility in representing alternative risk preferences (Meyer). With this utility function, the risk attitude measure is given by the marginal utility ratio of the utility function, $R(\pi,\sigma) = (\gamma/\theta)\pi^{1-\theta}\sigma^{\gamma-1}$. Risk aversion, neutrality, and affinity correspond to $\theta > 0$, $\theta = 0$, and $\theta < 0$, respectively. In the case of risk aversion, the magnitude of $R(\pi,\sigma)$ represents the degree of risk aversion. Decreasing absolute risk aversion, constant absolute risk aversion, and increasing absolute risk aversion are represented by $\theta > 0$, $\theta = 1$, and $\theta < 1$ while decreasing relative risk aversion, constant relative risk aversion, and increasing relative risk aversion are represented by $\theta > \gamma$, $\theta = \gamma$, and $\theta < \gamma$, respectively. The widely used linear mean-standard deviation model is a refutable special case of the MSD function, wherein γ =1 and $\theta = 1$.

The farmer observes past realization of the random returns to form a perception about the mean and standard deviation of the return distribution. Prior to the availability of SSTs all farmers use conventional practices and choose input use by maximizing (8) to find input application rates as:

$$Pf_x(x^C,\bar{z}) - w = (\gamma/\theta)\pi^{1-\theta}\sigma^{\gamma}P^2\left(\beta/2\exp(\beta x^C) + (\bar{z}\sigma_{\varepsilon}^{C})^2\, f_z(x^C,\bar{z})\, f_{xz}(x^C,\bar{z})\right). \tag{9}$$

If the farmer is risk neutral, i.e., $\gamma = 0$, the right-hand side of (9) is zero and the above first-order condition simply equates the expected marginal product to the input price.

To solve the model numerically we need to estimate the utility function and production function parameters. We obtain these parameters econometrically by specifying a production function $y = f(x,\bar{z};\alpha) + u$, where $Var(u) = \exp(\beta x)$ as assumed in our theoretical model above with α and β representing vectors of technology parameters. We obtain the first-order conditions in (9) for three inputs, nitrogen, phosphorus and potassium, which are then estimated jointly with the production function. The implicit estimation form of (9) is obtained by taking logarithms as:

$$\begin{aligned}&\ln\left[\left(P_j f_x(x_j,\bar{z}_j;\alpha)-w_j\right)\Big/\left(\beta/2\exp(\beta x_j)+(\bar{z}_j\sigma_{\varepsilon j}^C)^2 f_z(x_j,\bar{z}_j;\alpha)f_{xz}(x_j,\bar{z}_j;\alpha)\right)\right]-\ln(\gamma/\theta)\\&-2\ln P_j-(1-\theta)\ln\pi_j-\gamma\ln\sigma_j+\omega_j=0\end{aligned} \tag{10}$$

where the subscript j corresponds to the jth observation; ω_j denotes the error in optimization; and $(\sigma_{\varepsilon j}^C)^2=\left(Var(y_j)-\exp(\beta x_j)\right)\big/(\bar{z}_j f_z(x_j,\bar{z}_j;\alpha))^2$. The expression for σ_ε^C is derived from the variance of y ($y=f(x^C,\bar{z})+f_z(x^C,\bar{z})\bar{z}\varepsilon^C+u$). For efficiency gains, the system of three equations defined by (10) can be estimated together with the production function while recognizing the potential for correlated errors across the set of four equations.

To determine the technology structure several specifications of the Just-Pope function were estimated. These include the translog, Cobb-Douglas, and quadratic production functions. To keep our empirical model consistent with the theoretical framework above, we restricted the choice of specification to functions with a non-zero second derivative for all levels of input-use. Thus, linear-plateau and quadratic plateau functions were not used. Using Pollack and Wales' likelihood dominance criterion for testing non-nested hypothesis and Akaike's information criterion of model selection, the quadratic function was found to dominate the translog and Cobb-Douglas functions. Since the estimation procedure described above yields a nonlinear system of equations, convergence to a final set of estimates is difficult. Success in convergence and log likelihood dominance were key criteria in selection of the production technology. Using Pollack and Wales' likelihood dominance criterion for testing non-nested hypothesis and

Akaike's information criterion of model selection, the quadratic function was found to dominate the translog and Cobb-Douglas functions.

The following quadratic production function specification for three inputs; nitrogen (*N*), phosphorous (*H*) and potassium (*K*), and soil attribute, average potential yield, ($\bar{Z}$) was chosen:

$$y = \alpha_{1N} N + \alpha_{2N} N^2 + \alpha_{1H} H + \alpha_{2H} H^2 + \alpha_{1K} K + \alpha_{2K} K^2 + \alpha_{1Z} \bar{Z} + \alpha_{2Z} \bar{Z}^2 + \alpha_{NZ} \bar{Z} N + u \qquad (11)$$

where $Var(u) = \exp(\beta_0 + \beta_N N + \beta_H H + \beta_K K)$. In many areas, such as Illinois, soil nitrate tests have not been found to be successful in accurately measuring and predicting the available nitrogen in the soil. Recommendations for nitrogen application are instead based on the soil types in the field that determines its average maximum potential yield (Illinois Agronomy Handbook; Khanna, Isik and Winter-Nelson). We therefore include this average potential yield as an explanatory variable in the production function. We also examined the validity of including interaction terms between each type of fertilizer and average potential yield of the field. Only the interaction term between nitrogen and average potential yield was found to be significant; hence the other interaction terms were not included in the regression equation. The estimation of three first-order conditions obtained in (10) jointly with (11) provides efficient estimates of utility and production function parameters, with correlated errors and cross equation restrictions imposed during estimation.

The Data Set

The data set used to estimate the risk and technology parameters is obtained from a survey of farmers in the OtterLake watershed in Macoupin County, Illinois. All the farmers in the watershed, that includes about 7,370 acres of cropland, were contacted to obtain information about their field boundaries and about their yield and input application decisions at the field level for two years, 1993 and 1994. A 60% response rate limited our sample to 99 fields (covering

3,799 acres). All the fields were being cultivated using conventional practices. The survey provides data on the use of nitrogen, phosphorous and potassium, crop yields, average potential yields, average slope, topsoil thickness, and total soil thickness of each field. The spatial distribution of potential yields within each of the field boundaries was obtained using digitized soil maps. Each soil type has an associated estimate of corn yield potential (Olson and Lang). These maps provide distributions of soil quality represented by the potential crop yields. The summary statistics of the variables used in the estimation are given in Table 1.

Estimation Results

The nonlinear three-stage least squares procedure was used to jointly estimate (10) and (11), with the observations related to physical soil characteristics, total soil thickness, surface soil thickness and slope, being the exogenous variables (instruments) in the system. Initial values of the parameters in the system are crucial for obtaining convergence with a non-linear system of equations. These initial values of the production function are obtained using maximum likelihood estimation methods that provide a set of consistent estimates. The results from the joint estimation provide technology (α, β) and risk preference parameters (θ, γ). Most of the parameters of the mean and variance part of the production function are significant at 1% level (Table 2). The signs of the parameters in the term determining the variance of yield show how nitrogen, phosphorous, and potassium affect the variability of output.

The negative signs on the coefficients β_N and β_H show that nitrogen and phosphorous are risk-decreasing inputs, while potassium is a risk-increasing input ($\beta_K > 0$) under production uncertainty. Therefore, an increase in the use of nitrogen and phosphorous leads to a decrease in the variability of output while an increase in potassium use results in an increase in the variability of output. This is different from risk increasing/decreasing effect of an input with respect to uncertainty about soil conditions. In the literature, the empirical evidence with respect to risk-fertilizer relationship (under production uncertainty) is mixed. For example, Lambert found nitrogen to be risk decreasing with respect to production uncertainty while Nelson and Preckel and Love and Buccola found nitrogen to be risk increasing. Love and Buccola found phosphorous to be risk reducing while Nelson and Preckel found it to be risk increasing. On the other hand, potassium has been found to be risk increasing (Nelson and Preckel; Love and Buccola). The results from this study are similar to those of Lambert for nitrogen, Love and Buccola for phosphorous, and Nelson and Preckel and Love and Buccola for potassium. The implication of the results from this study is that a risk-averse farmer tends to increase the application of nitrogen and phosphorous while he tends to decrease the application of potassium under production uncertainty. The coefficient of the interaction term, α_{NZ} given in Table 2 is negative and statistically significant, indicating that soil quality represented by potential yield and applied nitrogen are substitutes each other. Since $\alpha_{NZ} < 0$, nitrogen is considered to be a risk-decreasing input under uncertainty about soil conditions when SSTs are adopted.

The risk-preference parameters given in Table 2, θ and γ, are found to be significantly greater than zero and equal to 1.13 and 1.64 respectively, rejecting the null hypothesis of risk-neutrality. Risk-neutrality would obtain as a special case if the parameter θ approaches one and γ approaches zero. The measure of risk aversion evaluated at the sample means is equal to 1.48 and shows that the degree of risk aversion does differ among farmers as shown in Table 2. The estimated risk-preference parameters are close to those found by Saha. To analyze the nature of risk aversion, several hypothesis tests are employed. First, the most commonly used linear mean standard deviation hypothesis, $H_0 : \theta = \gamma = 1$, is tested. The null hypothesis of linear mean standard deviation is rejected in favor of presence of nonlinear mean standard deviation. We also test whether farmers exhibit constant absolute risk aversion, $H_0 : \theta = 1$. The null hypothesis of constant absolute risk aversion is rejected. Another hypothesis tested is whether the farmers' risk preference is represented by constant relative risk aversion, i.e., $H_0 : \theta = \gamma$. The null hypothesis of constant relative risk aversion is also rejected. This implies that farmers in the OtterLake watershed exhibit decreasing absolute risk aversion and increasing relative risk aversion since $\theta > 1$ and $\theta < \gamma$. These findings are supported in the literature by a number of studies (Wolf and Pohlman; Saha, Shumway and Talpaz; Saha; Bar-Shira, Just and Zilberman). For example, decreasing absolute risk aversion and increasing relative risk aversion were also found by Saha, Shumway and Talpaz, and Saha for risk preferences of Kansas wheat producers and Bar-Shira, Just and Zilberman for risk preferences of Israeli farmers.

Economic and Environmental Impacts of SSTs under Uncertainty

The risk and technology parameters obtained above are used to examine the potential incentives for adoption of SSTs and its implications for fertilizer use by developing a simulation model. As shown in the theoretical model, the potential incentives for adoption of SSTs depend upon the uncertainty about soil conditions. The standard deviation of the random variable related to the uncertainty about soil conditions with conventional practices (σ_ε^C) is estimated using $(\sigma_\varepsilon^C)^2 = \left(Var(y) - \exp(\beta x)\right) / (\bar{z} f_z(x^C, \bar{z}))^2$ for each field. The value of σ_ε^C varies across the fields and is equal to 0.199 at the sample mean. The noise in the soil characteristics (ε^S) with adoption of SSTs is assumed to vary with the level of potential yield ($z_i \varepsilon^S$). The standard deviation of this random variable (σ_ε^S) is assumed to be 0.1. This value implies that standard deviation of the level of the soil attribute is equal to $0.1 z_i$, indicating that the level of potential yield could be 10% more or less than the measured level due to the measurement errors. For instance, for a section of the field with a true potential yield of 130 bushels/acre (that is unknown to the farmer), the farmer would consider it to lie, with a 68.3% probability, between 117 and 143 bushels/acre (which represent one-standard deviation levels on either side of the true level).

Because there is no information about distribution of soil fertility level (phosphorous and potassium) in the fields examined here, two alternative distributions of phosphorous and potassium (25% and 50% coefficients of variation) are generated using a Beta distribution as in Khanna, Isik, and Winter-Nelson. This study does not consider the possibility of measuring residual nitrogen in the soils (Illinois Agronomy Handbook; Khanna, Isik, and Winter-Nelson). However, nitrogen application rates vary with variations in the potential yields across the fields.

We examine the environmental implications of SSTs in terms of reducing nitrogen pollution. It is assumed that 0.75 lbs. of the applied nitrogen are absorbed by a bushel of corn and corn stover and that all excess nitrogen in the soil is available for leaching (Barry, Goorahoo and Goss; Khanna, Isik and Winter-Nelson). Thus, polluting run-off of the applied nitrogen per acre is given by $r = N - 0.75\, y$.

We assume that the farmer hires professional custom services for variable rate fertilizer applications. The per-acre cost of soil testing and mapping is assumed to be \$1.6 while the annual cost of variable rate fertilizer application is \$5.0 per acre (Illini FS). Thus, the per-acre annual cost of adopting SSTs is \$6.6. This value is within the range of \$3/acre and \$10/acre that is typically cited for the cost of SSTs (Swinton and Lowenberg-DeBoer). Prices of nitrogen, phosphorus and potassium are assumed to be \$0.2/lb, \$0.24/lb and \$0.13/lb, respectively while price of corn is set to \$2.5 per bushel (as in Khanna, Isik and Winter-Nelson; Pautsch, Babcock, and Breidt).

Quasi-rent Differentials under Risk-neutrality

The empirical model first examines the farm-level impacts of adoption of SSTs under risk-neutrality for the 99 fields with 25% coefficient of variations in the soil fertility distributions. In this simulation, adoption of SSTs is assumed to completely eliminate uncertainty about soil conditions, while conventional practices do involve uncertainty about soil conditions. Quasi-rents (revenue minus variable fertilizer costs) with conventional practices and SSTs are estimated by maximizing expected profits to find the optimal fertilizer applications. Table 3 presents the per-acre quasi-rent differentials of SSTs over conventional practices. The per-acre quasi-rent differentials with 25% coefficient of variations in the soil fertility distributions range between \$3.1 and \$18.2 across the fields examined here and the average quasi-rent differential is \$10.0 per acre[2]. Comparing the expected quasi-rent differentials to the per-acre costs of adoption (\$6.4) indicates that it would be optimal to adopt SSTs on 85.8% of the fields considered here under certainty about soil conditions with SSTs and risk-neutrality.

To examine the magnitude of the effect of the parameters of the distribution of potential yields on per-acre quasi-rent differentials of SSTs, $\Delta\pi$, as shown by (7) we estimate the following regression for these 99 fields:

$$\underset{(5.05)}{\Delta\pi=6.168}-\underset{(0.01)^*}{0.04\bar{Z}}+\underset{(0.03)^*}{0.246\delta}+\omega \qquad R^2=0.76 \tag{12}$$

where δ is the standard deviation of the potential yield distributions; standard errors are given in parenthesis; and * indicates that the estimated coefficient is significant at 1% level. It shows that fields with higher variability in soil quality distributions and a lower average level have higher

[2] We also examined the impacts of an increase in the variability of soil fertility distribution on the quasi-rent differentials. An increase in the coefficient of variation from 25% to 50% leads to an increase in the per-acre quasi-rent differentials from \$10 per acre to \$12.3 per acre. Throughout the rest of the paper, we report results obtained with 25% coefficient of variation, which is reasonable because soil samples collected in the fields of the two Illinois farms indicate that coefficient of variations of soil fertility distributions range between 22% and 45% (Ochai et al.)

quasi-rent differentials than others. Fields with lower average potential yield are likely to gain more from adopting SSTs. This could be because fields with lower quality soils and a lower average potential yield also have greater variability in soil types as observed by Babcock and Pautsch for fields in Iowa.

We now incorporate uncertainty about soil conditions with SSTs into the model with risk-neutrality. Under uncertainty about soil conditions with both SSTs and conventional practices and risk-neutrality, the quasi-rents of conventional practices and SSTs are estimated by maximizing expected profits. The per-acre quasi-rent differentials now vary between $2.7 and $15.3 across the fields. Comparing the quasi-rent differentials under certainty to those under uncertainty about soil conditions with SSTs we find that incorporation of uncertainty into the model leads to a reduction in the quasi-rent differentials. The average quasi-rent differential decreases from $10.0 per acre under certainty about SSTs and risk-neutrality to $8.5 per acre under uncertainty about soil conditions with SSTs and risk-neutrality. This occurs because uncertainty about soil conditions leads to an increase in the use of all fertilizers considered here, which increases the input costs and therefore reduces the quasi-rent differentials. In this case, 77.7% of the fields would find it to be profitable to adopt SSTs. We also examined the impact of an increase in σ_{ε}^{S} on the value of SSTs. An increase in σ_{ε}^{S} from 0.1 to 0.15 decreases the average quasi-rent differentials from $8.5 per acre to $6.7 per acre.

Quasi-rent Differentials under Uncertainty and Risk-Aversion

We first examine the impacts of SSTs on the quasi-rent differentials under risk aversion with production uncertainty and uncertainty about soil conditions with conventional practices. We assume that there is certainty about soil conditions with SSTs. We find in this case that per-acre quasi-rent differentials range from $1.7 to $10.8 across the fields examined here (Table 3).

The average quasi-rent differential decreased from $10.0 per acre under certainty and risk-neutrality to $6.5 per acre under production uncertainty and risk aversion. Risk aversion and production uncertainty result in a decrease in the quasi-rent differentials of all the fields since the applications of nitrogen and phosphorous increase while the application of potassium decreases. This increases fertilizer costs more than the revenue gains from increases in crop yields. Under production uncertainty and risk aversion, only 41.4% of the fields would switch from conventional practices to SSTs.

We now add uncertainty about soil conditions with SSTs to the model and present the results in Table 3. Uncertainty about soil conditions along with production uncertainty cause risk-averse farmers to increase the use of nitrogen and phosphorous and decrease the use of potassium. The average quasi-rent differential decreased from $10.0 per acre under certainty about soil conditions with SSTs to $5.0 per acre under uncertainty about production and soil conditions. The addition of uncertainty about soil conditions with SSTs to the model leads to further reductions in the quasi-rent differentials. Comparison of the expected utility with SSTs to that with conventional practices indicates that it would be optimal to adopt SSTs on only 15.2% of the fields considered here. Thus, risk aversion and uncertainties about soil conditions and production result in a substantial decrease in the quasi-rent differentials and adoption rates of SSTs. This implies that ignoring uncertainty about soil conditions with SSTs and production would lead to overestimation of the quasi-rent differentials and adoption rates of SSTs.

Environmental Implications of SSTs under Uncertainty

We now examine the impact of adoption of SSTs on nitrogen pollution generation. Under risk-neutrality and complete certainty about soil conditions with SSTs, adoption of SSTs leads to a reduction in the nitrogen pollution generation compared to the level with conventional application practices on all fields. Pollution reduction with adoption of SSTs as compared to conventional practices ranges between 1.1% and 42.3% across the fields (Table 4). Under uncertainty about soil conditions and risk-neutrality, pollution reduction with adoption of SSTs ranges between 0.8% and 40.9% across the fields. Average per acre pollution reductions with adoption of SSTs decreases from 19.8% under certainty about soil conditions with SSTs to 16.3% under uncertainty about soil conditions. Under production uncertainty and risk aversion, pollution reduction decreases substantially compared to the case of certainty and risk-neutrality. Adoption of SSTs now reduces nitrogen pollution between 0.5% and 24.7% across the fields. Average reduction in nitrogen pollution with adoption of SSTs decreases from 19.8% under certainty about soil conditions with SSTs to 12.5% under production uncertainty and risk aversion. This occurs because adoption of SSTs leads to an increase in the application of nitrogen and phosphorous while it leads to a decrease in potassium use. These changes in fertilizer use do not lead to a significant increase in crop yields and therefore in input uptake by crops to offset the increases in the nitrogen use. Hence, nitrogen pollution with adoption of SSTs increases substantially relative to the case with no uncertainty. However, it is still lower than that with conventional practices on most of the fields.

Pollution reduction under uncertainty about production and soil conditions is much lower than in the case of certainty about soil conditions with SSTs and risk-neutrality and on a few fields pollution increases with adoption of SSTs (Table 4). This occurs because uncertainty about soil conditions results in an increase in the nitrogen application while crop yields obtained do not increase as much to offset the increase in the application of nitrogen due to changes in other inputs. Therefore, adoption of SSTs could lead to an increase in the nitrogen pollution under uncertainty about soil conditions and risk aversion. Average reduction in nitrogen pollution with adoption of SSTs decreases from 19.8% under certainty about soil conditions with SSTs and risk-neutrality to 8.3% under both production and soil conditions uncertainty with risk aversion. Hence, ignoring uncertainty about soil conditions and production would lead to overestimation of nitrogen pollution reduction with SSTs.

Cost-share Subsidies Under Uncertainty and Risk Aversion

Table 4 also presents the cost-share subsidy required to induce adoption of SSTs. The required subsidies to induce adoption of SSTs vary across heterogeneous fields as shown above. Under risk-neutrality and no uncertainty about soil conditions with SSTs, the quasi-rent differentials of most of the fields examined here exceed the per-acre cost of adoption; thus there is need for cost-share subsidies to induce adoption of SSTs for only a few fields. The average subsidy as a percentage of the total cost in this case is 5.2%. Under uncertainty about soil conditions and risk-neutrality, average subsidy required to adopt SSTs increases to 6%. However, under production uncertainty and risk aversion, a much higher subsidy is necessary to induce adoption of SSTs. The average subsidy rate estimated as a percentage of the cost of adoption of SSTs is 23.2%. The average subsidy rates required increased from 5.2% under certainty about soil conditions with SSTs and risk-neutrality to 50.1% under uncertainty about production and soil conditions. Under uncertainty and risk-aversion, higher subsidies are necessary to induce adoption of SSTs due to the need to compensate for the risk premium, which also varies across heterogeneous farmers.

Conclusions

This paper develops a model of farmer-decision making to analyze the incentives for adoption of a technology that provides information about spatial variability in nutrient availability within a field and enables corresponding variable rate applications of fertilizers within that field. It examines the extent to which risk aversion and uncertainties about production and the accuracy of the technology have impacts on input applications and adoption decisions of SSTs and how these impacts vary with the characteristics of the soil distribution in the field. The paper also examines the potential policy relevance of considering uncertainty and risk-aversion by examining the design of cost-share subsidies to achieve reductions in nitrogen pollution. By taking into account uncertainty about soil conditions and production as well as risk preferences, it provides an explanation for the low observed adoption rates of SSTs among farmers.

The model uses jointly estimated risk and technology parameters to estimate the impacts of SSTs on returns and nitrogen pollution generation. The quasi-rent differentials vary across the fields due to the differences in soil quality distributions. The gain in quasi-rents from SSTs is higher on fields with low potential yield and high spatial variability. Adoption of SSTs under uncertainty about production and soil conditions would lead risk-averse farmers to apply more fertilizers and generate more pollution on the fields with low variability in soil quality distribution. Ignoring the impact of uncertainty about soil conditions with SSTs and risk preferences leads to a significant overestimation of the economic and environmental benefits of SSTs and underestimation of the required cost-share subsidies for adoption of SSTs. Improving the technical accuracy of SSTs through reducing the uncertainty about soil conditions has the potential to improve the economic and environmental benefits of SSTs as well as to increase the incentives for adoption of SSTs.

The results obtained herein show that SSTs have the potential to reduce nitrogen pollution relative to conventional practices but in the presence of uncertainty about weather and soil conditions in the field, the incentives to over-apply nitrogen can considerably reduce the environmental gains from SSTs. Hence, improved information about weather patterns and reduced uncertainty about technical accuracy of SSTs would enable better realization of the potential benefits of SSTs. While the feasibility of reducing these uncertainties and their costs are not examined here, this paper shows that the potential benefits of reducing these uncertainties should include both the private benefits for farmers through increased profits from adoption and the social benefits through reduced nitrate run-off from agricultural production practices.

Table 1. Summary Statistics on Data Used to Estimate the Risk and Technology Parameters[a]

Variables	**Mean (Standard Deviation)**
Yield (bushel per acre)	158.17(30.72)
Potential Yield (bushel per acre)	163.41(22.11)
Nitrogen (pounds per acre)	172.09(47.40)
Phosphorous (pounds per acre)	61.45(47.57)
Potassium (pounds per acre)	106.96(71.01)
Surface Soil Thickness (inches)	8.06 (1.42)
Total Soil Thickness (inches)	63.07 (11.63)
Slope (%)	5.54 (5.27)

[a] The number of observations is 198.

Table 2. Parameter Estimates and Test Results

Parameter	Description	Estimate
α_{1N} α_{2N} α_{1H} α_{2H} α_{1K} α_{2K} α_{1Z} α_{2Z} α_{NZ}	Production Function Parameters-Mean[a]	1.166(0.3489)* -0.009(0.0029)* 0.5268(0.1361)* -0.0047(0.0013)* 0.2243(0.0576)* -0.0011(0.0002)* 1.0244(0.2526)* -0.0022(0.0012)*** -0.0009(0.00042)**
β_N β_H β_K β_0	Production Function Parameters-Variance[a]	-0.0041(0.0014)* -0.0142(0.0032)* 0.00859(0.0049)** 6.7054(0.5971)*
θ γ	Utility Function Parameters[a]	1.1263(0.0204)* 1.63676(0.0304)*
$H_0 : \theta = \gamma = 1$	Linear MSD Model[b]	2780.226(0.000)
$H_0 : \theta = 1$	CARA Preferences[c]	6.1912(0.000)
$H_0 : \theta = \gamma$	CRRA Preferences[d]	29.6256(0.000)
$R(\pi, \sigma)$ evaluated at the sample mean	Risk Aversion Measure[a]	1.479(0.423)*

*Significant at 1%. **Significant at 5%. ***Significant at 10%.
[a] Standard errors in parentheses.
[b] Asymptotic Chi-square square statistics, P-value in parentheses.
[c] Constant Absolute Risk Aversion, asymptotic t-statistics, *P*-value in parentheses.
[d] Constant Relative Risk Aversion, asymptotic t-statistics, *P*-value in parentheses.

Table 3. Per Acre Quasi-rent Differentials of SSTs, Adoption Rates, and Difference in Risk Premiums[a]

		Certainty About Soil Conditions with SSTs and Risk-Neutrality	Uncertainty About Soil Conditions with SSTs and Risk-Neutrality	Production Uncertainty and Risk Aversion	Uncertainty about Production and Soil Conditions with Risk Aversion
Quasi-rent Differentials ($ Per Acre)	**Min**	3.1	2.7	1.7	1.1
	Average (Standard Deviation)	10.0 (3.3)	8.5 (3.0)	6.5 (1.7)	5.0 (1.6)
	Max	18.2	15.3	10.8	7.6
Adoption Rates (%)[b]		85.8	77.8	41.4	15.2

[a] Coefficient of variations in the soil fertility distributions is 25%. Conventional application practices involve uncertainty about soil conditions.

[b] Represents the percentage of the 99 fields that would switch from conventional practices to SSTs after taking into account the costs of adopting SSTs.

Table 4. Percentage Per Acre Nitrogen Pollution Reductions with Adoption of SSTs as Compared to the Pollution Level under Conventional Practices and Required Cost-Share Subsidies[a]

		Certainty About Soil Conditions with SSTs and Risk-Neutrality	Uncertainty About Soil Conditions with SSTs and Risk-Neutrality	Production Uncertainty and Risk Aversion	Uncertainty about Production and Soil Conditions with Risk Aversion[b]
Percentage Nitrogen Pollution Reductions with SSTs	**Min**	1.1	0.8	0.5	-2.0
	Average (Standard Deviation)	19.8 (7.9)	16.3 (7.7)	12.5 (6.6)	8.3 (6.0)
	Max	42.3	40.9	24.7	19.0
Required Cost-Share Subsidies as Percentage of Total Costs (%)	**Min**	0.0	0.0	0.0	0.0
	Average (Standard Deviation)	5.2 (4.8)	6.0 (5.5)	23.2 (9.0)	50.1 (9.8)
	Max	53.0	59.1	74.2	83.3

[a] Coefficient of variations in the soil fertility distributions is 25%. Conventional application practices involve uncertainty about soil conditions.
[b] Negative numbers indicate that adoption of SSTs increases nitrogen pollution.

References

Asche, F., and R. Tveteras. "Modeling Production Risk with a Two-Step Procedure." *Journal of Agricultural and Resource Economics*, 24(1999): 429-439.

Babcock, B.A. "The Effects of Uncertainty on Optimal Nitrogen Applications." *Review of Agricultural Economics*, 14(July 1992): 270-280.

Babcock, B.A., A. L. Carriquiry and H. S. Stern. "Evaluation of Soil Test Information in Agricultural Decision-making." *Applied Statistics*, 45(1996): 447-461.

Babcock, B.A., and G.R. Pautsch. "Moving from Uniform to Variable Fertilizer Rates on Iowa Corn: Effects on Rates and Returns." *Journal of Agricultural and Resource Economics*, 23(1998): 385-400.

Babcock, B.A., and J. F. Shogren. "The Cost of Agricultural Production Risk." *Agricultural Economics*, 12(1995): 141-150.

Barry, D.A.J., D. Goorahoo, and M.J. Goss. "Estimation of Nitrate Concentration in Groundwater Using a Whole Farm Nitrogen Budget." *Journal of Environmental Quality*, 22 (1993): 767-775.

Bar-Shira , Z., R.E. Just, and D. Zilberman. "Estimation of Farmers' Risk Attitude: An Econometric Approach." *Agricultural Economics*, 17(1997): 211-222.

Bontems, P. and A. Thomas. "Information Value and Risk Premium in Agricultural Production: The Case of Split Nitrogen Application for Corn." *American Journal of Agricultural Economics*, 82(2000): 59-70.

Bullock, D.G., and D. S. Bullock. "Quadratic and Quadratic-Plus-Plateau Models for Predicting Optimal Nitrogen Rate of Corn: A Comparison?" *Agronomy Journal*, 86(1994): 191-195.

Dai, Q. J.J. Fletcher, and J.G., Lee. "Incorporating Stochastic Variables in Crop Response Models: Implications for Fertilization Decisions." *American Journal of Agricultural Economics*, 75 (1993): 377-386.

English, B.C., S.B. Mahajanashetti, and R. K. Roberts. "Economic and Environmental Benefits of Variable Rate Application of Nitrogen to Corn Fields: Role of Variability and Weather." Selected Paper for the Annual Meeting of the American Agricultural Economics Association, Nashville, TN, August 8-11, 1999.

Feder, G. "Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty." *Oxford Economic Papers*, 32(1980): 265-283.

Fixen, P.E., and H.F. Reetz. "Site-specific Soil Test Interpretation Incorporating Soil and Farmer Characteristics." In Proceedings from the 2nd International Conference, March 27-30, Minneapolis, MN, p. 731-743, ASA/CSSA/SSSA, 1995.

Hennessy, D.A. and B. A. Babcock. "Information, Flexibility, and Value Added." *Information Economics and Policy*, 10(1998): 431-449.

Harvey, A.C. "Estimating Regression Models with Multiplicative Heteroscedasticity." *Econometrica*, 44(1976): 461:65.

Illini FS Agricultural Cooperative, http://www.illinifs.com.

Illinois Agronomy Handbook. University of Illinois at Urbana-Champaign, Department of Crop Sciences, Cooperative Extension Service, 1998.

Isik, M. "Resource Management under Production and Output Price Uncertainty: Implications for Environmental Policy." *American Journal of Agricultural Economics*, 84(August 2002): 558-572.

Just, R.E., and R.D. Pope. "Stochastic Specification of Production Functions and Economic

Implications." *Journal of Econometrics,* 7(February 1978): 67-86.
Just, R.E. and D. Zilberman. "Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture." *Oxford Economic Papers,* 35(1983): 307-328.
Katz, E. "On Variability under Certainty." *European Economic Review,* 26 (1984): 109-113.
Khanna, M., M. Isik, and A. Winter-Nelson. "Investment in Site-Specific Crop Management Under Uncertainty: Implications for Nitrogen Pollution Control and Environmental Policy." *Agricultural Economics*, 24(2000): 9-21.
Karagiannis, G. "Interactions between Agricultural and Resource Policy: Comment." *American Journal of Agricultural Economics,* 80(May 1998): 419-421.
Lambert, D. and J. Lowenberg-DeBoer. "Precision Agriculture Profitability Review." Site-specific Management Center, School of Agriculture, Purdue University, 2000.
Lambert, D. K. "Risk Considerations in the Reduction of Nitrogen Fertilizer Use in Agricultural Production." *Western Journal of Agricultural Economics*, 15(2): 234-244.
Leathers, H.D., and J.C. Quiggin. "Interactions between Agricultural and Resource Policy: The Importance of Attitudes toward Risk." *American Journal of Agricultural Economics,* 73(August 1991): 757-764.
Love, H. A. and S. T. Buccola. "Joint Risk Preference-Technology Estimation with a Primal System." *American Journal of Agricultural Economics*, 73(1991): 765-774.
Lowenberg-DeBoer, J. and A. Hallman. "Value of pH Soil Sensor Information." in Proceedings of the Fifth International Conference on Precision Agriculture and Other Precision Resource Management, July 15-19, 2000.
Meyer, J. "Two-Moment Decision Models and Expected Utility Maximization." *American Economic Review,* 77(June 1987): 421-430.
Nelson, C.H. and P.V. Preckel. "The Conditional Beta Distribution as a Stochastic Production Function." *American Journal of Agricultural Economics,* 71(1989): 370-78.
Ochai, S., R. H. Hornbaker, D. G. Bullock, and T. Ellsworth. "Economic Value of Site-Specific P and K Information Under Alternative Soil Sampling." in Proceedings of the Fifth International Conference on Precision Agriculture and Other Precision Resource Management, July 15-19, 2000.
Olson, K.R., and J. M. Lang. Productivity of Newly Established Illinois Soils, 1978-1994, Supplement to Soil Productivity in Illinois, Department of Agronomy, University of Illinois at Urbana-Champaign, 1994.
Pollack, R.A. and T.J. Wales. "The Likelihood Dominance Criterion: A New Approach to Model Selection." *Journal of Econometrics,* February/March 1991, 227-42.
Pope, R.D. and R.A. Kramer. "Production Uncertainty and Factor Demands for Competitive Firms." *Southern Economic Journal*, 46(1979): 489-501.
Ramaswami, B. "Production Risk and Optimal Input Decisions." *American Journal of Agricultural Economics*, 74(1992): 860-869.
Robison, L. J. and P.J. Barry. The Competitive Firm's Response to Risk, Macmillan Publishing Company, New York, 1987.
Saha, A. "Risk Preference Estimation in the Nonlinear Mean Standard Deviation Approach." *Economic Inquiry*, 35(1997): 770-782.
Saha, A., C.R. Shumway, and H. Talpaz. "Joint Estimation of Risk Preference Structure and Technology using Expo-Power Utility." *American Journal of Agricultural Economics,* 76(1994): 173-184.
Schnitkey, G. D., J.W. Hopkins, and L.G. Tweeten. "An Economic Evaluation of Precision

Fertilizer Applications on Corn-Soybean Fields" in Proceedings of the Third National Conference on Precision Agriculture, June 23-26, 1996, edited by P.C. Robert, R.H. Rust, and W.E. Larson, 1996, American Society of Agronomy.

Searcy, S.W., J.K. Schueller, Y.H. Bae, S.C. Borgelt, B.A. Stout. "Mapping of Spatially-Variable Yield During Grain Combining." *Trans ASAE*, 32(1989): 826-829.

Swinton, S. M., and J. Lowenberg-DeBoer. "Evaluating the Profitability of Site-Specific Farming." *Journal of Production Agriculture*, 11(1998): 439-446.

Thrikawala, S., A. Weersink, G. Kachnoski, and G. Fox. "Economic Feasibility of Variable Rate Technology for Nitrogen on Corn." *American Journal of Agricultural Economics*, 81(1999): 914-927.

Wolf, C. and L. Pohlman. "The Recovery of Risk Preferences from Actual Choices." *Econometrica*, 51(1983): 843-50.