United States
Department of
Agriculture

Economic
Research
Service

Resources and
Technology
Division

# Economic and Environmental Effects of Nitrogen Testing for Fertilizer Management

Darrell J. Bosch
Keith O. Fuglie
Russ W. Keim



Water Quality

The United States Department of Agriculture (USDA) prohibits discrimination in its programs on the basis of race, color, national origin, sex, religion, age, disability, political beliefs, and marital or familial status. (Not all prohibited bases apply to all programs.) Persons with disabilities who require alternative means for communication of program information (braille, large print, audiotape, etc.) should contact the USDA Office of Communications at (202) 720-5881 (voice) or (202) 720-7808 (TDD).

To file a complaint, write the Secretary of Agriculture, U.S. Department of Agriculture, Washington, DC 20250, or call (202) 720-7327 (voice) or (202) 720-1127 (TDD). USDA

**Economic and Environmental Effects of Nitrogen Testing for Fertilizer Management**. By Darrell J. Bosch, Keith O. Fuglie, and Russ W. Keim. Resources and Technology Division, Economic Research Service, U.S. Department of Agriculture. Staff Report No. AGES9413.

## Abstract

Concern about nonpoint source pollution of water resources has resulted in a search for new technologies and farming practices that can reduce agriculture's contribution to pollution and enhance environmental quality. This report assesses the potential of information technology (soil and tissue nitrogen testing) to improve nitrogen (N) fertilizer management and reduce N losses to the environment. A simultaneous equations model is developed to assess factors associated with the adoption of N testing and the impact of N testing on N fertilizer use, corn yields, and net returns to corn growers. Implications of N testing for environmental quality are also derived.

**Keywords**: Nitrogen fertilizer, nitrogen testing, water quality, production risk, technology adoption, switching regression

## Acknowledgments

We would like to thank Robbin Shoemaker, Wen-yuan Huang, and Utpal Vasavada for their useful comments on an earlier draft of this paper, and Sharon Lee for editorial assistance, without implicating them in any remaining shortcomings.



Washington, DC 20005-4899 April 1994

## Contents

# Economic and Environmental Effects of Nitrogen Testing for Fertilizer Management

by

Darrell J. Bosch, Keith O. Fuglie, and Russ W. Keim[1]

## Introduction

Agriculture is increasingly viewed as an important contributor to nonpoint source pollution of water bodies through the leaching and runoff of agricultural chemicals and fertilizers (Office of Technology Assessment). One way to reduce the environmental costs of agricultural production is to develop and apply technologies that will enable farmers to more accurately match the amount and timing of input use to crop production needs. Such technologies often take the form of information technologies, such as soil nutrient testing, pest scouting, and soil moisture testing. The use of an information technology in and of itself does not enhance farm productivity or environmental quality. Its effect in achieving these goals comes about through its effect on the improved allocation of agricultural production inputs. This study examines the use of nitrogen (N) testing in N fertilizer management and explores the consequences of adoption for farm productivity and environmental quality.

These issues carry important implications for public policy. The consequences of farmers' production decisions on water quality are shared by others. Thus, the water quality benefits from adopting new information technology may not be fully reflected in the decisions by individual farmers. Although farmers may choose to adopt information technologies due to the private incentives from increased production efficiency, it is not clear that private benefits alone will lead to a socially optimum rate of adoption. Public policies that require the use or subsidize the cost of using these technologies may be necessary in order to achieve environmental goals. To be most effective, public policies, to encourage the adoption of information technologies, need to be targeted to those farms and regions in which the social benefits are high but where market incentives are low.

This study examines the economic and environmental implications of soil and tissue N testing in N fertilizer management. N testing is an information technology that can enhance water quality by improving the efficiency of N fertilizer use. The ability to accurately estimate N requirements is particularly important because N is susceptible to both leaching into groundwater and runoff into surface water. High concentrations of N in water

---

[1] Bosch is associate professor of Agricultural Economics, Virginia Polytechnic Institute and State University, Blacksburg, VA. Fuglie and Keim are agricultural economists, Resources and Technology Division, Economic Research Service, U.S. Department of Agriculture, Washington, DC.

bodies pose a health risk (Cantor) and degrade ecosystems (National Research Council, 1978). More sophisticated N management tools may help reduce farmers' costs and increase net returns as well as reduce social costs caused by N leaching and runoff. The specific objectives of the study are to: (1) identify factors associated with the adoption of N testing; (2) determine how adoption of N testing has affected N fertilizer use, crop yields, and net returns; (3) evaluate the environmental implications of N testing; and (4) examine whether the private incentives for N test adoption are sufficient to achieve a socially optimum level of adoption.

The next section summarizes recent developments in N testing technology and reviews previous studies on the effectiveness of N testing for supporting crop N recommendations. A conceptual model of N use is then developed to analyze how the value of better information on soil N may affect N fertilizer application and N losses to the environment. Next, an empirical assessment of N testing is made using farm-level data from the U.S. Department of Agriculture's Area Studies Survey. A simultaneous equations model is estimated to examine the adoption of N testing among corn growers in selected areas of Nebraska, Indiana, and Pennsylvania and to determine the effects of N-test adoption on N fertilizer use, crop yields, and net returns. These results are used to derive implications of N testing on potential N losses to the environment. The final section summarizes the major findings and discusses some policy implications.

## Information and N Application Decisions

### Recommending Crop N Applications

N application recommendations for corn, one of the most important crops to which N is applied, are generally based on an N balance equation such as the following (Meisinger and others):

$$N_f = (N_{ch} + N_{cr} - e_m N_{\min} - e_s N_{\sin}) / e_f \tag{1}$$

where $N_f$ is fertilizer N, $N_{ch}$ is N in harvested grain, $N_{cr}$ is N in crop stover, $N_{min}$ is estimated soil N mineralization, $e_m$ is the fraction of $N_{min}$ in the above-ground crop, $N_{sin}$ is estimated soil inorganic N, $e_s$ is the fraction of $N_{sin}$ in the above-ground crop, and $e_f$ is the fraction of $N_f$ in the above-ground crop. Traditional approaches may attempt to estimate $N_{min}$ and $N_{sin}$ based on field history by taking account of previous legume crops and manure applications (Magdoff and others). However, soil testing has traditionally not been used to estimate soil N contributions because of the complex behavior of soil N and uncertainty about changes in availability of N between the time of a soil test and when the crop requires N (Beegle and others).

### Preplant Soil N Test (PPNT)

Concern about the economic losses and environmental damage caused by N applications in excess of crop requirements has led to development of soil and plant tissue testing procedures. Two types of soil N tests have been developed: the preplant N test (PPNT) and presidedress N test (PSNT). The PPNT was initially developed in subhumid areas of the Western United States where lower annual precipitation and deeper topsoil profiles enable more accurate predictions of soil N availability for crops (Meisinger and others; Hergert). It is also used in western and northern portions of the Corn Belt where conditions favor the accumulation and retention of inorganic N (Bundy and others). These conditions include lower annual precipitation compared with the Eastern United States and the fact that soils are frozen for 3 to 4 months per year (Bundy and others). Ideally, sampling should be done as close to planting as possible to account for any N losses over the winter (Meisinger and others). It is recommended that sampling be done at depths of up to 2 to 3 feet (Bundy and others). The estimated N in the soil profile is generally subtracted from the N application recommendation, although the precise procedure may vary by State (Bundy and others).

Mixed results are reported as to the effectiveness of the PPNT. The test has been shown to be effective in the Western United States and has been used there for over 20 years (Meisinger and others; Hergert). Tests in Wisconsin and Minnesota have also found that the PPNT can be used to more accurately predict crop N requirements (Bundy and others). However, Hoeft and others found that the PPNT frequently did not improve the ability to predict optimal crop N applications in the eastern Corn Belt.

Presidedress Soil N Test (PSNT)

The PSNT, which has been developed for use on corn in humid areas of the United States, differs from the PPNT in several ways. Testing is conducted when corn is 6 to 12 inches tall, which is late enough to minimize the probability of changes in soil N availability before the N is required by the crop, yet early enough to allow additional N to be applied before maximum crop uptake (Beegle and others). The test is typically done by sampling the top 12 inches of soil (compared with 2 or more feet for the PPNT). The PSNT attempts to measure N mineralization intensity, while the PPNT attempts to measure total mass of available soil N before planting (Meisinger and others).

A general approach is to recommend N applications based on the yield goal and the level of soil nitrate N predicted by the PSNT (Magdoff and others; Fox and others). In some States, the PSNT is used only to determine if soil nitrate N exceeds a critical level. If the critical level is exceeded, no additional N is recommended. If soil nitrate N is below the critical level, a conventional recommendation is made based on yield goal and credits for manure and legumes (Fox and others).

The PSNT has been found to be effective in lowering N applications by identifying soils where crops will or will not respond to additional N (Fox and others; Blackmer and others; Magdoff and others). It is particularly helpful in predicting the mineralization of organic N from previous manure applications (Fox and others). Legg found that sites with manure application often had N applied in excess of agronomic recommendations for the yield goal and that this over-application was related to lack of farmer awareness of the N content of manure. Either the PPNT or PSNT may be particularly effective in determining the amount of N to credit to previous manure applications in determining commercial fertilizer N applications to the current crop. Surveys have also found that there is substantial farmer satisfaction with the PSNT (Magdoff and others). Shortle and others found that 36 percent of

Pennsylvania farmers surveyed had used the PSNT and that the test caused N applications to corn to decline by an average of 42 pounds/acre, or by about 50 percent. Budget analysis of survey results indicated that the profits of survey farmers were increased an average of $3.82 per acre as a result of using the PSNT (Shortle and others).

Evaluation of the PSNT under field conditions in Pennsylvania over 1989-91 indicated that the test reduced N applications by 60 pounds/acre in 1991 when dry conditions resulted in lower-than-normal N losses through leaching and denitrification. In 1989, the test reduced average applications by only 15 pounds/acre because of higher-than-normal N losses to leaching and denitrification due to wet weather (Shortle and others). Budget analysis of these results indicated that average profits increased by an average of $13.53 per acre over the 3 years (Shortle and others).

The PSNT is subject to errors of two types. The more commonly observed error is predicting that a field will respond to applied N when in fact it does not (Fox and others). This error may occur because (1) nitrate N is leached below the portion of soil profile sampled but not below the root zone, and (2) mineralization of organic N increases after sampling (Magdoff and others). A second type of error is predicting a field will not respond to N when in fact it does. This error may be caused by leaching of nitrate N out of the root zone after sampling (Magdoff and others).

The adoption of PSNT is hindered by several factors (Hoeft and others). Labor is required for collection of samples at a time when farmers are busy with other work. Collection of representative samples is difficult on fields where commercial N or manure is injected. Delaying N application until test results are received may be risky, if wet conditions prevent N side-dressing. For some situations, the test may not be informative, that is, it may not improve accuracy in predicting optimal N application rates, particularly where a continuous corn or corn-soybean rotation is produced without manure and where spring rains are not excessive. Commercial fertilizer dealers may not be interested in carrying out the test because it may lower their sales (Magdoff and others).

**Plant Tissue Testing**

Tissue testing for N is similar to the soil N tests in that it attempts to derive field-specific N recommendations based on measurable conditions. Two types of plant tests are the end-of-season stalk test and the leaf test. The leaf test is nearly as accurate as the PSNT in separating fields into those that will and will not respond to N (Fox and others). However, it has a greater tendency to indicate that fields would not respond to N when in fact a response could be obtained (Fox and others). The leaf test may be best suited to conditions where N can be applied frequently throughout the season ("spoon-feeding") perhaps through the irrigation system. The test can be done regularly to indicate if the plant is suffering an N deficiency, and small doses of N can be applied accordingly (Schepers and others). The end of season stalk test is used to help adjust N applications in the following growing season (Blackmer and others). The test measures nitrate concentrations in the stalk to evaluate N applications during the preceding season. If stalk nitrate concentrations exceed a critical range, applications were too high and can be lowered in the following year (Blackmer and others).

### Soil N Testing Costs

Soil N testing costs will depend on the number of samples required, the number of cores taken per sample, and the depth of the sample. It is recommended that 10 to 20 cores be taken for a composite sample for a field of up to 20 acres (Hergert; Beegle and others; Bundy and others). Sample analysis costs \$6 per sample (Shortle and others). Assuming that 1 hour is required to take sample cores for a field and that labor costs \$6 per hour, then total costs for drawing and analyzing samples are \$12 per field or approximately \$0.60 per acre. If field size is smaller than 20 acres, the same number of sample cores and samples are required on smaller fields as on the 20-acre field. For example, if the field were 10 acres, sample cost would be \$12 divided by 10 acres or \$1.20 per acre.

## Conceptual Model of N Application

### Effects of N Testing on N Applications

The conceptual model of N application is kept simple in order to focus attention on the effects of better information on N use. The model assumes that N application is always possible after the result of the soil N test is known. Thus, the model is more relevant to the PPNT than the PSNT. Assume farmers produce a crop Y with one variable input, N. They choose the amount of N to add to the soil ($N_a$) in order to maximize profits. The crop's N response function is described as $Y = f(N_a)$ where $f' > 0$ and $f'' < 0$. Profits ($\pi$) are defined as:

$$\pi = P_Y \cdot f(N_a) - P_N \cdot N_a \tag{2}$$

where $P_N$ and $P_Y$ are N fertilizer price and crop price, respectively. Other fixed costs are ignored because they are not affected by the N application decision. Farmers are assumed to be technically efficient. The optimal N application is the level at which the marginal value product of N equals its factor price:

$$f'(N_a) \cdot P_Y = P_N \tag{3}$$

Next, assume that N can also be provided from a stock of available N in the soil, $N_s$, and that $N_s$ is a perfect substitute for $N_a$. Without soil testing, the amount of $N_s$ is uncertain and is assumed to be either high ($N_{sh}$) or low ($N_{sl}$) with equal probability. We assume there are no biases in the farmers' subjective probabilities, that is, no tendency to overestimate the probability of either a high or low stock of N. Crop yield and profits for a given level of N application are uncertain because of uncertainty about $N_s$. If the farmers are risk neutral (Hey), their objective is to choose an N application level with no information, $N_{ani}$, that maximizes expected profits $E_{ni}(\pi)$ defined as:

$$E_{ni}(\pi) = [\theta\cdot f(N_{sl} + N_{ani}) + (1 - \theta)\cdot f(N_{sh} + N_{ani})]\cdot P_Y - P_N\cdot N_{ani} \quad (4)$$

where $f(N_{sl} + N_{ani})$ and $f(N_{sh} + N_{ani})$ denote crop response to applied N when the soil N stocks are low and high, respectively.

For simplicity, assume that there is an equal probability of low and high states of soil N ($\theta = 0.5$). Then expected profit is maximized where:

$$0.5\cdot[f'(N_{sl}+N_{ani}) + f'(N_{sh}+N_{ani})]\cdot P_Y = P_N \quad (5)$$

That is, optimality occurs where the weighted sum of the marginal value products under both states equals the factor price.

Now assume that farmers obtain information on the state of soil N prior to applying $N_a$. With the information, the yield for each level of N application can be predicted with certainty. After obtaining information, an N application rate is selected so that the marginal value product (MVP) of N (soil N plus applied N) is less than or equal to the price of applied N. If the MVP of soil N is above the price of N, then $N_a$ will be added. If the MVP of soil N is already equal to or below the price of N, then N fertilizer application will be zero.

Figure 1 illustrates two possible cases. Let $N^*$ be the point where the MVP of total available N equals the cost of N fertilizer. With information about soil N, the optimal amount of N applied when soil N is high is $N_{aih}$ and when soil N is low is $N_{ail}$. Because f(N) is concave in N ($f'' < 0$), $N_{aih}$ is less than $N_{ail}$. In figure 1a, soil N is below $N^*$ in both the high and low soil N state. In this case, N is applied in both states but is lower when soil N is high. In figure 1b, soil N in the high state is above $N^*$ and no additional N will be applied. N is still added in the low state.

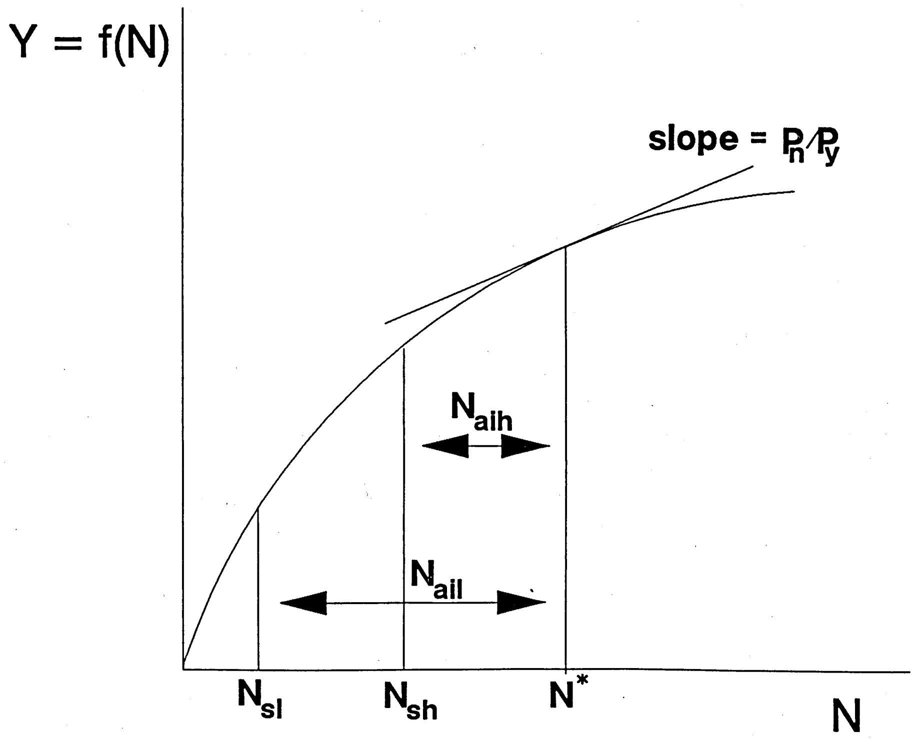
Given the equal probability of high and low states, the average N application with information, $N_{ai}$, is:

$$\overline{N}_{ai} = 0.5\cdot(N_{aih} + N_{ail}) \quad (6)$$

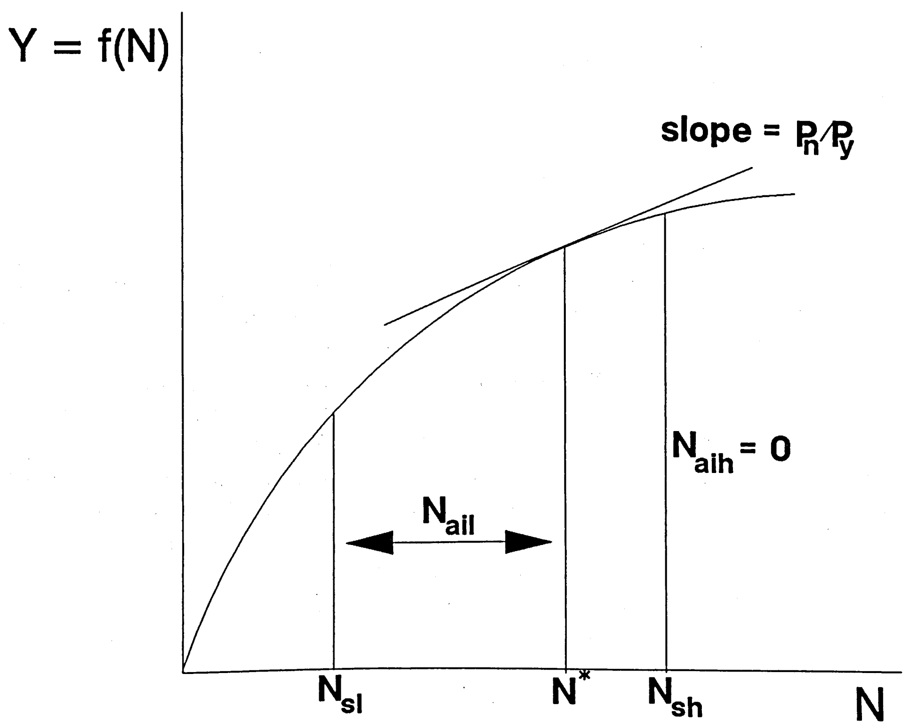
With information about the amount of available soil N, average N applications could decrease, remain the same, or increase, depending on the shape of the production function. $N_{ai}$ will be greater than, equal to, or less than $N_{ani}$ (the amount of N applied without information) if the marginal product of N is declining at an increasing, constant, or decreasing rate, respectively. Consider the case where the marginal product is declining at a decreasing rate, that is, $f''' < 0$. We show that the expected application with information ($N_{ai}$) is less than the application without information using three steps: (1) start with the expected application with information ($N_{ai}$) set equal to the application with no information $N_{ani}$; (2) maximize expected profits subject to the constraint that $N_{ai} = N_{ani}$; and (3) compare expected MVP's of N to show that relaxing the constraint and allowing $N_{ai}$ to fall below $N_{ani}$ will increase profits.

Figure 1. N fertilizer applications with low and high soil N states

1a




1b



Step one. If $\bar{N}_{ai}$ is set equal to $N_{ani}$, the amount applied when soil N is high is $N_{ani} - \Delta N$, while the application when soil N is low is $N_{ani} + \Delta N$.

Step two. Assume that $\Delta N$ is chosen to maximize profits subject to the constraint that $N_{ai}$ equals $N_{ani}$. Profits are maximized for a $\Delta N$ such that:

$$MVP(N_{sl} + N_{ani} + \Delta N) = MVP(N_{sh} + N_{ani} - \Delta N) \qquad (7)$$

Because soil N and applied N are perfect substitutes, the N application will be lowered in the high soil N state and increased in the low N state until total N (soil plus applied) is equal in both states and the MVP's of applied N are also equal.

Step three. Because the marginal product of N declines at a decreasing rate, a reduction in N application when soil N is high causes less of an increase in marginal product than the decrease in marginal product caused by increasing the N application when soil N is low. Algebraically, this relationship is expressed as:

$$MVP(N_{sh} + N_{ani} - \Delta N) - MVP(N_{sh} + N_{ani}) < MVP(N_{sl} + N_{ani}) - MVP(N_{sl} + N_{ani} + \Delta N) \qquad (8)$$

This situation occurs if total N (soil plus applied) in the low soil N state is less than total N in the high soil N state. Rearranging the terms in the previous equation:

$$MVP(N_{sh} + N_{ani} - \Delta N) + MVP(N_{sl} + N_{ani} + \Delta N) < MVP(N_{sh} + N_{ani}) + MVP(N_{sl} + N_{ani}) \qquad (9)$$

The terms on the left side of the inequality represent MVP's of N with information and the terms on the right side MVP's of N without information. Taking expectations given that each state has equal probability:

$$E_i(MVP(N)) < E_{ni}(MVP(N)) \qquad (10)$$

If farmers attempt to keep expected N applications with information equal to the level without information, the expected MVP falls below its level without information and below the price of N. Thus, in order for first-order conditions to hold, the expected N application with information will fall below the constant N application without information.

When the marginal product of N declines at a constant rate ($f''' = 0$), each unit of N added to the amount applied with no information in the low N state causes the marginal product to go down by the same amount as the marginal product goes up when the N application is decreased in the high soil N state. Expected MVP remains constant and the amount of N applied without information equals the expected amount applied with information. Finally, if the marginal product of N declines at an increasing rate ($f''' > 0$), increases in MVP caused by reducing N applications in the high N state will be greater than reductions in MVP caused by increasing N applications in the low N state. The expected MVP will increase and exceed the price of N. Therefore the expected N applications with information must be greater than the amount applied without information in order to make the expected MVP of N applications with information equal the price of N.

In this model, the marginal product of N must be declining at a decreasing rate ($f'''(N) < 0$) in order for information to cause average N applications to decline. In fact, some commonly used functional forms (such as the logarithmic function) are characterized by $f''' > 0$, while others such as the quadratic have $f''' = 0$. For more general function forms, such as the translog, $f'''$ can be positive or negative. However, the analysis does not consider the effects of nonneutral risk attitudes that may affect N applications and are discussed in a later section.

**Value of Information Concerning N Available for Plant Growth**

The value of information from a soil N test is the difference in profits with and without information on soil N levels. Ignoring fixed costs, expected profits without information are defined in equation 4. Average profits with information are:

$$E_I(\pi) = 0.5\cdot[\,(f(N_{sl} + N_{ail}) + f(N_{sh} + N_{aih}))\cdot P_Y - P_N\cdot(N_{ail} + N_{aih})\,] - C \qquad (11)$$

The net value of information is $V = E_i - E_{ni}$. If the cost of conducting the test, C, is zero, then the value of information will be nonnegative. Furthermore, assuming C is zero, the value of information will be positive if the information causes the pattern of N use to change from N use with no information. Information implies higher profits because it allows the MVP of N to be equated to its price in all soil N states.

If C is positive, then it is not possible to say a priori whether the net value of information is always positive, that is, whether the increased profits from more efficient allocation of N are always sufficient to offset the cost of the test. C may be large, especially when the cost of the time (that of the farm manager or someone else) required for taking samples is considered.

**Risk Aversion, Information, and N Use**

Risk-averse producers are willing to sacrifice some amount of expected net income in order to reduce risk (Hey). Consider a producer who equates risk with the variance of income.[2] Then following Robison and Barry, the objective function can be described as maximizing the certainty equivalent of net income as shown below:

---

[2] Meyer discusses one important condition under which equating risk with variance will give the same results as a more general expected utility model based on all moments of the outcome distribution. This condition is that two distributions of the random outcome that result from different decisions differ by only location and scale.

$$Max\ CE(\pi) = E(\pi) - (\lambda/2)\cdot\sigma_\pi^2 \tag{12}$$

where $\lambda$ is the coefficient of absolute risk aversion (Pratt) and $\sigma_\pi{}^2$ is the variance of net income. Assuming that N is the only variable input, the certainty equivalent of net income can be expressed as:

$$Max\ CE(\pi) = P_Y\cdot E[f(N_a+N_s)] - P_N\cdot N_a - (\lambda/2)\cdot\sigma^2\cdot P_Y^2 \tag{13}$$

The variance in net income is caused by yield variability ($\sigma^2$) due to uncertain soil N levels (prices are assumed known). The certainty equivalent of net income is maximized with regard to N application when:

$$P_y\cdot E(f'(N_a + N_s)) - (\lambda/2)\cdot P_y^2\cdot(\partial\sigma^2/\partial N_a) = P_N \tag{14}$$

$P_Y^2$ is positive as is $\lambda$ for the risk averter. The sign of $\partial\sigma^2/\partial N_a$ is negative because of the concavity of the production function (Robison and Barry). Larger applications of N cause the spread between high and low yields in the high and low soil N states, respectively, to decline because the marginal productivity of N is declining. Because this term is negative, the certainty equivalent is maximized for the risk averter where the expected MVP of N is less than its price. For the risk-neutral producer, $\lambda$ equals 0 and the certainty equivalent is maximized where the expected MVP of N equals its price. Because the expected MVP is less for the risk averter than for the risk-neutral producer and because the MVP of N is declining, N use for the risk averter will exceed that for the risk-neutral producer. However, a risk seeker whose coefficient of absolute risk aversion is negative maximizes the certainty equivalent where the expected MVP of N exceeds its price. The risk seeker's N use is less than that of the risk-neutral producer. These results are based on the assumption that the only source of risk is uncertainty about soil N levels and could change if other sources of risk are introduced, such as the interaction between N response and weather.[3]

When the soil N state is the only source of uncertainty, information reduces the variance of yield to zero because the yield for a given N application is known once the soil N state is known. With information, the third term in the above equation, $(\lambda/2)P_Y^2(\partial\sigma^2/\partial N_a)$, is set to zero, which tends to reduce N use by the risk averter. It is not certain that N use goes down with better soil N information. As discussed under the risk-neutral case, when the marginal product of N falls at an increasing rate ($f'''(N) > 0$) and the expected N application with information is set equal to the application without information, the expected MVP of N with information will exceed that with no information by some amount k. If k is less than $(\lambda/2)P_Y{}^2(\partial\sigma^2/\partial N_a)$, then

[3] Lambert found that N increased net income risk when both price and yield were risky, implying that risk averters would use less N than risk seekers. Reducing N increased the variance of yield. However, reducing N lowered expected yield and, therefore, the exposure to price risk, causing the overall variance of net income to decline.

information will cause N use to decline when risk attitudes of the producer are considered.

Table 1 summarizes the expected effects of information on N use for different types of production functions and risk attitudes based on the model and assumptions described above. Farmers who are risk averse will always reduce N use, except when the MVP declines at an increasing rate, in which case the effects of information are indeterminate. Risk-neutral farmers reduce N use when the MVP of N declines at a decreasing rate, do not change N use when the MVP falls at a constant rate, and increase N use when the MVP declines at an increasing rate. Farmers who are risk seekers will increase N use with information, unless MVP declines at a decreasing rate, in which case the effects of information are unpredictable.

Risk aversion makes it more likely that farmers' N use with information will decline. Wilson and Eidman found 44 percent of a sample of farmers to be risk averse, while 22 percent were risk seeking. Tauer found 36 percent of farmers were risk averse compared with 26 percent risk seekers, with the remainder in the two studies being risk neutral. Thus, although the conceptual model presented here does not allow definitive conclusions about the effects of information on N use, better information is likely to reduce N use by many farmers.

**Table 1 -- Effects of soil N information on N applications**

| Farmers' attitude toward risk | Change in expected N application | | |
|---|---|---|---|
| | MVP of N falls at a decreasing rate | MVP of N falls at a constant rate | MVP of N falls at an increasing rate |
| Risk averse | Negative | Negative | ? |
| Risk neutral | Negative | No change | Positive |
| Risk seeker | ? | Positive | Positive |

**Information and Potential N Pollution**

The previous analysis considered the effects of soil test information on N applications but not on the potential for N pollution. The soil N test is likely to have greater probability of reducing N pollution losses than of reducing N applications. Potential for N pollution is likely to be reduced because in those cases where the N test indicates the need for greater N applications than would otherwise be applied, it is likely that much of the additional N will be used by the crop. When the test indicates that N applications can be reduced, much of the reduction would otherwise have been lost to pollution.

For example, assume as before that $Y = f(N_a + N_s)$ where $f' > 0$ and $f'' < 0$.

The assumption that $f'' < 0$ implies that as more N is applied less of each additional unit applied is taken up by the crop.[4] Let P represent the portion of each unit of N that is not removed by the harvested portion of the crop and that can potentially be lost to pollution. P increases with N (that is, $\partial P/\partial N > 0$). Given a constant N application, potential losses from the last unit of N applied in the high soil N state, $P_h$, will be higher than such losses in the low soil N state, $P_l$. Assume that the test causes N applications to increase in the low soil N state and decrease in the high soil N state, but that the expected N application remains constant before and after the test ($N_{ai} = N_{ani}$). For each unit of applied N reallocated from the high to the low soil N state, expected pollution losses will be reduced because $\partial P/\partial N > 0$. The reduction in potential N losses continues as long as total N (applied plus soil) is less in the low soil N state than in the high state. Total N losses with the test are lower than previously, even though expected N applications are the same with and without the test. Even if expected N applications increase after the soil N test, the potential for N losses could be lower if the reduced losses from reallocation of N applications from the high to low soil N state more than offset increased potential losses from the higher expected N application.

**Special Considerations for the Presidedress N Test (PSNT)**

The analysis of the PSNT that is available for corn is more complicated than that of the PPNT. Use of the PSNT may require N to be added in two stages, once before and once after obtaining the uncertain test results. The added cost and inconvenience of a second N application will be necessary, if the PSNT indicates the need for more N. In addition, N applications after obtaining test results can be made only during a relatively short period, while the crop is small enough to permit mechanical application. Possible wet weather during this period may not allow all the desired N to be applied and a yield loss may occur. Feinerman and others demonstrate that when N and plant available soil moisture are substitutes, risk-averse farmers will apply more N at planting compared with risk-neutral farmers, because of the risk of not being able to apply N later in the season. They do not consider the possibility of obtaining additional information from a soil N test.

Shortle and others found that when there is perfect information about N availability and no limit on days available for side-dressing, generally all N will either be side-dressed or applied preplant but not both. All N will be side-dressed as long as the per-unit cost of side-dressed N is less than the per-unit cost of preplant N, divided by the proportion of preplant N applied that is available to the plant at the side-dressing stage. Shortle and others note that it is not possible to determine analytically whether shifting from preplant applications to side-dressing will increase or reduce N applications and N losses. Feinerman and others and Shortle and others found that

---

[4]For example, in the case of corn, as plant-available N increases, there is a tendency for the N content of stalks to increase (Blackmer and others). If stalks are not harvested, as is the case with corn grain production, and if the higher N content is not considered in determining N applications to following crops, there will be greater potential for N losses when N applications are increased.

consideration of uncertain field day availability for side-dressing makes it possible that combined preplant and side-dress applications will be optimal. Both studies imply that uncertainty about field day availability for N side-dressing may partially negate the benefits of information from the PSNT.

## Data for Empirical Analysis of N Testing

### Description of Data Set

Data for an empirical analysis of N testing are from the 1991 Area Studies Survey conducted by the U.S. Department of Agriculture (USDA). The Area Studies Survey is a collaborative effort of the USDA's Soil Conservation Service (SCS), National Agricultural Statistics Service (NASS), and Economic Research Service (ERS), and the U.S. Department of Interior's Geological Survey (USGS) to investigate relationships between agricultural practices and water quality. In the 1991 survey, an area sampling frame was used to select a sample of points from four major watersheds in the United States: the Lower Susquehanna River Basin (in Pennsylvania and a small part of Maryland), the White River Basin (in Indiana), the Central Nebraska Basins, and the Mid-Columbia River Basin (in Washington State and a small part of Idaho). These watersheds are part of the National Water Quality Assessment (NAWQA) Program of the USGS. Figure 2 shows the locations of the 1991 Area Studies Survey sites, along with the sites that have been selected for surveys in 1992 and 1993.

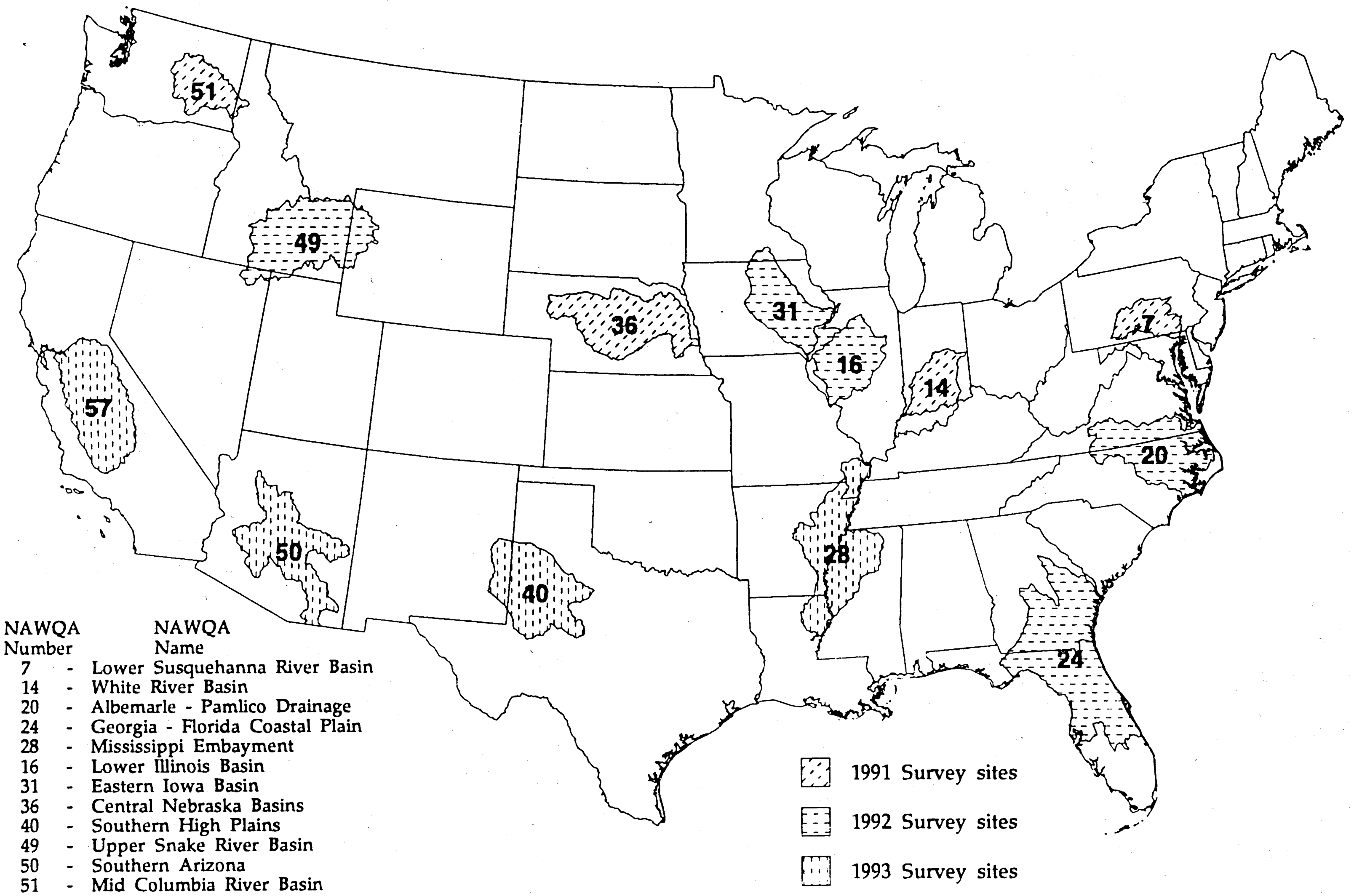
In 1991, a total of 3,428 questionnaires were completed. For each questionnaire, a personal interview was conducted with the farm operator to determine cropping practices during the previous three years and general information about the farm operation. Soil and topographical characteristics of the sampled points were collected by the SCS as part of the National Resources Inventory.

In the statistical analysis, the sampled fields were weighted so that they are spatially representative of the watersheds. The weight is equal to the inverse of the probability that the point was selected times the size of the primary sample unit in which the point fell. For the present study on the analysis of N testing and N fertilizer use, fields that were planted to field corn in either 1990 or 1991 were selected. Corn is the major user of N fertilizer in the United States (Vroomen and Taylor). However, if a field was planted to corn in both 1990 and 1991, only the 1991 data for that field were used (to avoid serial correlation). The selected sample consists of 1,169 fields, of which 566 are located in Indiana's White River Basin, 449 are from the Central Nebraska Basins, 149 from the Lower Susquehanna River Basin in Pennsylvania, and 5 from the Mid-Columbia River Basin in Washington (below, the watersheds will be referred to by the State in which they are primarily located).

### N Management Information and N Testing

The survey asked farmers to indicate the most important source of information they use in making their N fertilizer management decisions. The possible responses were:

# Figure 2. USDA Area Studies Survey sites




| NAWQA Number | | NAWQA Name |
|---|---|---|
| 7 | - | Lower Susquehanna River Basin |
| 14 | - | White River Basin |
| 20 | - | Albemarle - Pamlico Drainage |
| 24 | - | Georgia - Florida Coastal Plain |
| 28 | - | Mississippi Embayment |
| 16 | - | Lower Illinois Basin |
| 31 | - | Eastern Iowa Basin |
| 36 | - | Central Nebraska Basins |
| 40 | - | Southern High Plains |
| 49 | - | Upper Snake River Basin |
| 50 | - | Southern Arizona |
| 51 | - | Mid Columbia River Basin |
| 57 | - | San Joaquin-Tulare Basins |

(a) no N applied,
(b) fertilizer company recommendation,
(c) consultant recommendation,
(d) judgment based on crop appearance,
(e) judgment based on soil or tissue test,
(f) Extension Service recommendation,
(g) standard amount for the crop when in this rotation, and
(h) other.

The responses were divided into three "levels" of information, depending upon our judgment about the kind of expertise involved in N management. Survey responses are summarized in figure 3. N management based primarily on a farmer's own judgment and experience was categorized as using a relatively low level of information. This included farmers who based their N fertilizer application rates on a standard amount or on the crop's appearance. This is the most common source of information for N management among sampled farms, and accounted for nearly half of all responses. The next level of information involves using professional advice (either from an agricultural extension agent, a professional crop consultant, or a fertilizer company representative). At the second level, farmers combine their own experience with the judgments of individuals who specialize in fertilizer management. About 25 percent of surveyed corn farmers reported using these services as the principal source of information for N management. The highest level of information (according to our judgment) is to use chemical analysis (soil or tissue N tests) to determine crop fertilizer needs. Just over 20 percent of farmers in the sample rely on soil or tissue N testing for their N management decisions. The remaining farmers either did not apply N fertilizer or did not specify a method for determining their N fertilizer application decisions (this group is not shown in figure 3).

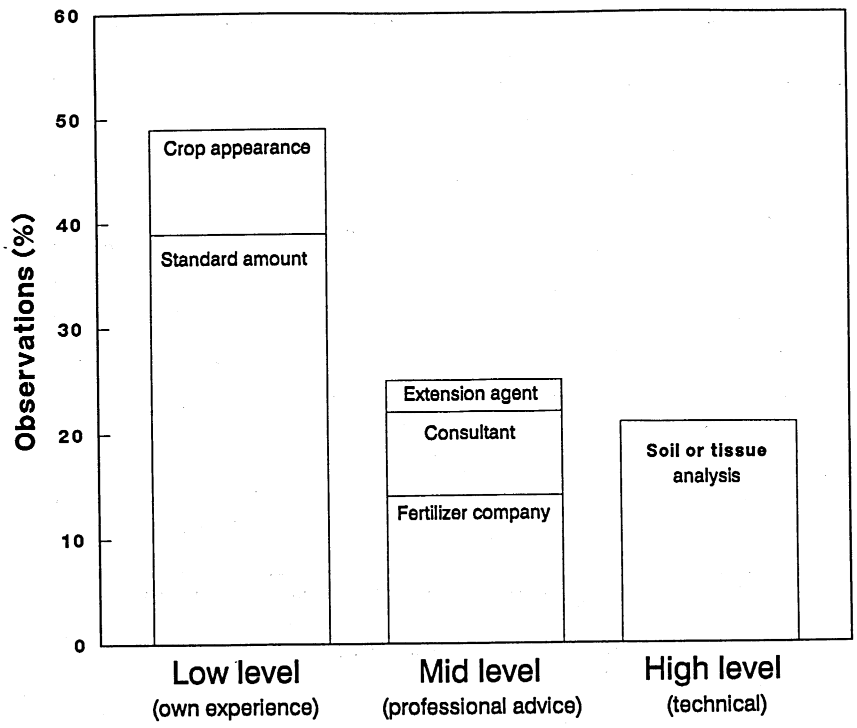
Figure 4 shows the frequency of N testing for irrigated and unirrigated corn farms in Nebraska, and corn farms in Indiana and Pennsylvania. A field was considered to have an N test if a soil N test had been conducted at any time between the end of the growing season in the previous year and the end of the growing season in the current year, or if a tissue test had been conducted during the current growing season. In Nebraska, over 60 percent of irrigated corn fields and 23 percent of unirrigated fields reported using N testing. Percentages were lower in the other areas. Sixteen to seventeen percent of farms used N testing on the surveyed corn fields in Indiana and Pennsylvania.

Timing and depth of soil N tests varied across areas. Nearly 80 percent of the tests were taken either in the first 3 months or last 3 months of the year, with March and November being the most frequently cited months. Depth of soil tested varied, with deeper soil profiles being tested in the Western States. Average depth was over 3 feet in Washington, nearly 2 feet in Nebraska, and less than 1 foot in Indiana and Pennsylvania.

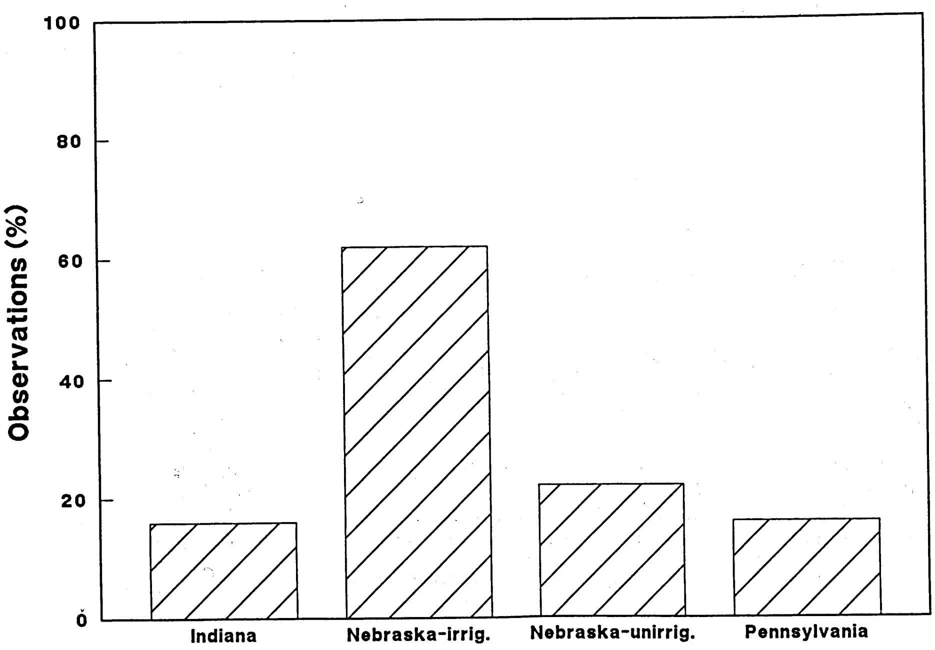
## N Fertilizer Use and Crop Yields

Figure 5 shows mean application rates of N fertilizer to corn for N test adopters and nonadopters. In Nebraska and Indiana, farms that used N tests applied less N fertilizer compared with farms that did not N test. The largest difference in N application rates between adopters and nonadopters

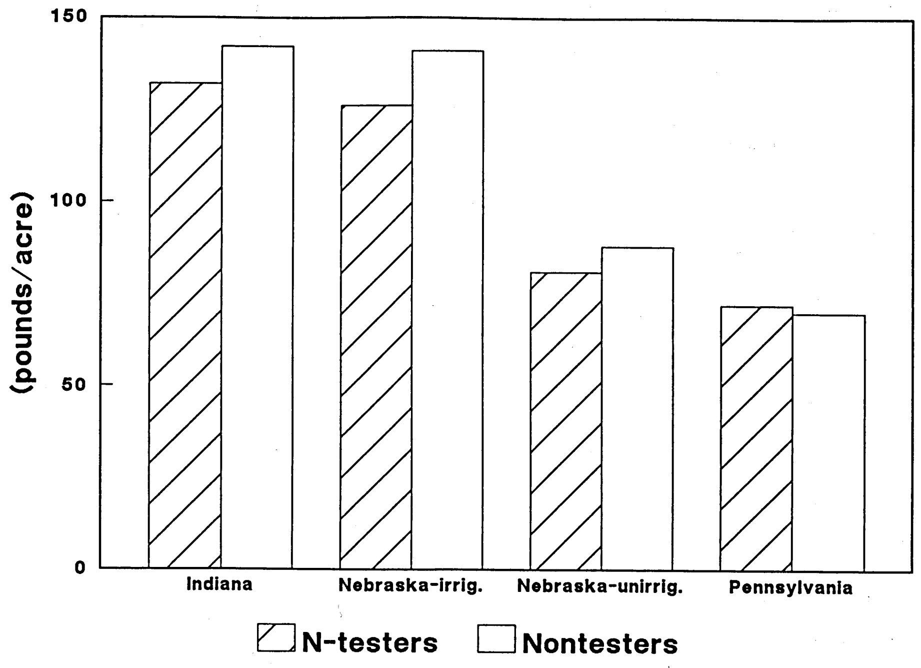
## Figure 3. Principal sources of information for N management



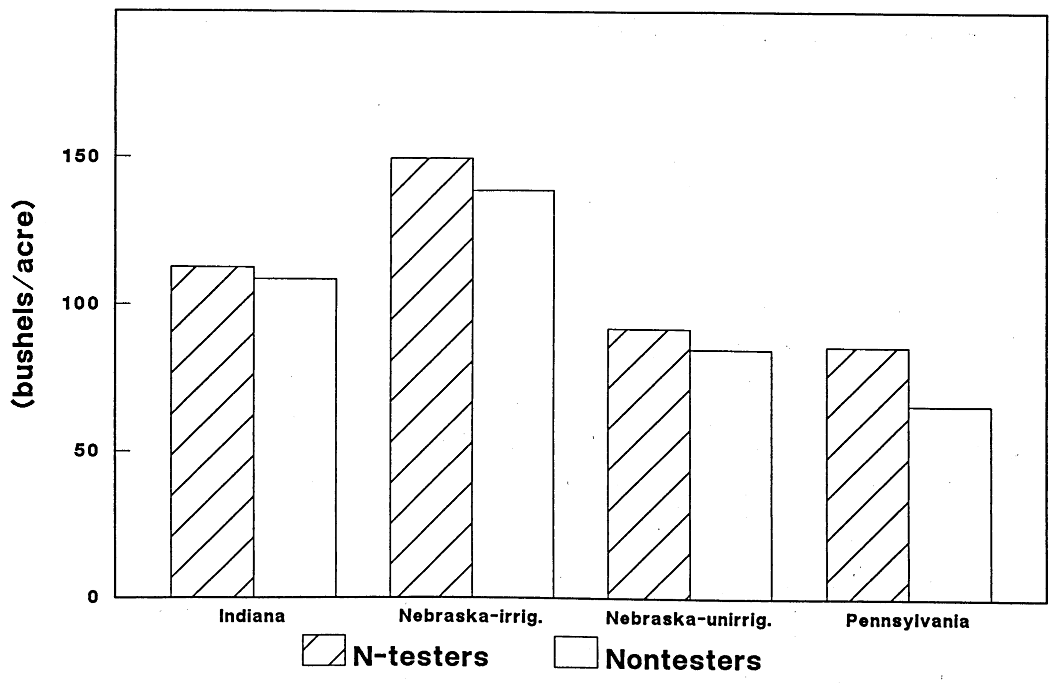

## Figure 4. Adoption of N testing in corn production



## Figure 5. N testing and N fertilizer use




## Figure 6. N testing and corn yields



occurred among irrigated Nebraska farms. Among this group, farms that did not N test applied an average of 140 pounds of N/acre, while farms that did test for N applied about 125 pounds/acre. In Pennsylvania, there was no appreciable difference in N fertilizer application rates among adopters and nonadopters. The differences in corn yields among N testers and nontesters are shown in figure 6. In all areas, farms that tested for soil or tissue N reported higher average yields than farms that did not N test. In Pennsylvania, yields on farms that conducted N tests were about 33 percent higher, at 80 bushels/acre versus 60 bushels/acre for other farms. In the other areas, yields were 5 to 15 bushels/acre higher on farms that tested for N.

These differences in average N fertilizer application rates and crop yields between farms that did and did not conduct N tests may not necessarily be due to the adoption of N testing. Other factors, such as cropping history, previous manure applications, soil quality, and managerial ability of the farmer, will influence crop yields and fertilizer rates and may also be correlated with N testing. For example, farmers who previously applied manure may be more likely to use less N fertilizer and get higher yields whether or not they conduct an N test. They may also be more likely to conduct an N test as an added assurance on the availability of mineralized N for the current crop. In the next section, an econometric model is presented that allows for a more rigorous assessment of the impact of adoption of N testing by controlling for the effects of correlated factors.

## Empirical Model

### Simultaneous Equations Model of Technology Adoption

Adoption of new technology can often be modeled as a dichotomous choice variable, which is the outcome of a utility or profit metric. Let the farmer's belief concerning the utility of adoption be given by $I_n^*$ and the utility of nonadoption be given by $I_o^*$. A farmer adopts the new technology if $I_n^* > I_o^*$ and does not adopt if $I_n^* \leq I_o^*$. What is observed, however, is the technology choice decision I where $I = 1$ if $I_n^* > I_o^*$ and $I = 0$ if $I_n^* \leq I_o^*$. The profitability of adoption is determined by a set Z of exogenous variables that influence the performance of the technology on a farm and the costs of adopting the new technology, including learning costs. Variables in Z include measures of farm size, land quality, human capital, risk preferences, and other socioeconomic and resource characteristics of a farm. Z may also include agricultural price and policy variables that affect the utility or profitability of adoption (Rogers; Feder and others; Feder and Umali). Technology adoption then becomes:

$$I = Z'\gamma + \varepsilon \tag{15}$$

where $\gamma$ is a vector of parameters and $\varepsilon$ is an error term with mean 0 and variance $\sigma^2$. $\varepsilon$ includes measurement error and factors that are unobserved by the econometrician but known to the farmer. Equation 15 is based on the notion that firms are heterogeneous in their characteristics, and not all firms find it profitable or convenient to adopt a new technology (at least not at the same time). Although ordinary least squares (OLS) estimates of equation 15 will be biased, equation 15 can be consistently estimated using a limited dependent variable model such as binomial probit (Maddala).

In many situations, adoption of a new technology can affect the parameters of input demand and output supply functions. For example, Pitt found that adoption of high-yielding varieties increased the elasticity of fertilizer demand. Also, the adoption of a new technology may create interaction effects between the observed variables in X and unobserved factors affecting the adoption decision. One type of unobserved variable may be input or resource quality. For example, suppose that a new technology is most suitable on farms with a high degree of water control. A researcher may observe the presence of an irrigation system, but not have complete information on the quality of the system. High-quality irrigation (an unobserved factor) is likely to be associated with higher fertilizer responsiveness and use (an observed variable) and may also be correlated with a higher adoption rate of fertilizer management technology such as soil nutrient testing.

Let Y = f(X) represent the relationship between a decision variable Y (input demand, crop supply, profits, etc.) and a vector of exogenous factors X (prices, fixed factors, etc.). One equation is specified for adopters and another for nonadopters:

$$\begin{aligned} Y &= X'\beta_n + \varepsilon_n \quad \text{if } I = 1 \\ Y &= X'\beta_o + \varepsilon_o \quad \text{if } I = 0 \end{aligned} \tag{16}$$

However, OLS estimates of equation 16 cannot be used to predict the effects of adopting the new technology. The differences between $\beta_n$ and $\beta_o$ measure not only the effects of adoption but also the fact that the set of adopting firms may be systematically different from the set of nonadopting firms, due to the effects of sample selection bias. In other words, the error terms in equation 16, conditional on the sample selection criterion, have nonzero expected values (Lee; Willis and Rosen; Maddala). Furthermore, equations 15 and 16 form a system of simultaneous equations. But standard methods, such as two-stage least squares, will be biased because equation 15 involves a dichotomous choice variable (Maddala).

Lee's approach treats sample selectivity as a missing variables problem. The error terms are assumed to have a joint-normal distribution with the following variance-covariance structure:

$$cov(\varepsilon_n, \varepsilon_o, \varepsilon) = \begin{bmatrix} \sigma_n^2 & \sigma_{no} & \sigma_{nc} \\ & \sigma_o^2 & \sigma_{oc} \\ & & \sigma^2 \end{bmatrix} \tag{17}$$

where $\text{var}(\varepsilon_n) = \sigma_n^2$, $\text{var}(\varepsilon_o) = \sigma_o^2$, $\text{var}(\varepsilon) = \sigma^2$, $\text{cov}(\varepsilon_n, \varepsilon_o) = \sigma_{no}$, $\text{cov}(\varepsilon_n, \varepsilon) = \sigma_{nc}$, and $\text{cov}(\varepsilon_o, \varepsilon) = \sigma_{oc}$. Given these assumptions, the expected values of the truncated error terms $(\varepsilon_n | I=1)$ and $(\varepsilon_o | I=0)$ are:

$$E(\varepsilon_n | I = 1) \;=\; E(\varepsilon_n | \varepsilon > -Z'\gamma) \;=\; \sigma_{nc} \frac{\psi(Z'\gamma/\sigma)}{\Phi(Z'\gamma/\sigma)} \;\equiv\; \sigma_{nc}\,\lambda_n \tag{18}$$

$$E(\varepsilon_o | I = 0) \;=\; E(\varepsilon_o | \varepsilon \leq -Z'\gamma) \;=\; \sigma_{oc} \frac{-\psi(Z'\gamma/\sigma)}{1 - \Phi(Z'\gamma/\sigma)} \;\equiv\; \sigma_{oc}\,\lambda_o \tag{19}$$

where $\Psi$ and $\Phi$ are the probability density function and cumulative density function of the standard normal distribution, respectively. Equations 18 and 19 are considered to be missing variables in equation 16. By finding instruments for these variables, they can be added to the specification of equation 16 and then equation 16 can be consistently estimated with OLS.

Lee suggested a two-stage method to estimate the model. In the first stage, a probit model of the adoption equation $I = Z'\gamma + \varepsilon$ is estimated to provide estimates of $\gamma$. Although the probit model does not provide an independent estimate of $\sigma^2$ (the probit model only estimates $\gamma/\sigma$), it can be assumed that $\sigma^2 = 1$ without affecting the results of the rest of the model. The estimates from equation 15 can be used to estimate $\lambda_n$ and $\lambda_o$ according to the definitions in equations 18 and 19. In the second stage, these variables are added to the appropriate equation in equation 16 and the following are estimated by OLS:

$$\begin{aligned} Y &= X'\beta_n + \sigma_{nc}\,\lambda_n + \eta_n \quad \text{if } I = 1 \\ Y &= X'\beta_o + \sigma_{oc}\,\lambda_o + \eta_o \quad \text{if } I = 0 \end{aligned} \tag{20}$$

Given the assumptions of the model (particularly the assumption of a joint-normal error distribution), the estimates of $\beta_n$ and $\beta_o$ given by equation 20 capture the effects of adopting the new technology. The coefficients of the variables $\lambda_n$ and $\lambda_o$ provide estimates of the covariance terms $\sigma_{nc}$ and $\sigma_{oc}$, respectively. The residuals $\eta_n$ and $\eta_o$ can be used to estimate $\sigma_n$ and $\sigma_o$ (formulas for this estimation procedure are given in Maddala). Note, however, that $\sigma_{no}$, the covariance between $\varepsilon_n$ and $\varepsilon_o$ cannot be estimated, since there are no observations that appear in both regimes. As an alternative to the two-stage estimation procedure described above, the model can also be estimated by maximum likelihood (ML) methods. While both the two-stage and ML approaches give consistent estimates of the parameters, the ML estimator is more efficient (that is, it has the smallest possible variance in the class of unbiased estimators). The likelihood function for an observation in this model is:

$$Prob[\varepsilon > -Z'\gamma | Z, X, \varepsilon_n] * f(\varepsilon_n) \;+\; Prob[\varepsilon \leq -Z'\gamma | Z, X, \varepsilon_o] * f(\varepsilon_o) \tag{21}$$

where $f(\varepsilon_i)$ is the probability density function of $\varepsilon_i$ for i=(o,n).

The identification criterion for the switching regression model is that there should be at least one variable in Z that does not appear in X. However, in many situations, it is likely that X and Z will contain the same variables since the factors that affect the utility or profitability of adoption are also likely to affect the input demand and supply functions. Pitt suggested including higher ordered terms in the adoption equation to achieve identification. In the present study, identification is achieved by including in Z policy variables that are designed to encourage adoption of N testing but that do not affect input use directly.

The switching regression model provides evidence on how Y (profit, supply, or input demand) changes when a new technology is adopted. For a firm that has adopted the new technology and with characteristics (X,Z), the expected value of the $Y_n$ is:

$$E(Y_n|I = 1) = X'\beta_n + \sigma_{nc}\lambda_n \tag{22}$$

The last term takes into account sample selectivity, that is, the fact that a firm that has adopted the technology may behave differently from an average firm with characteristics (X,Z) due to unobserved factors.

The predicted value of $Y_o$ for this firm, that is, the expected value of Y that the firm would have chosen had it not adopted the technology, is:

$$E(Y_o|I = 1) = X'\beta_o + \sigma_{oc}\lambda_n \tag{23}$$

Thus, the change in Y due to adoption is given by:

$$E(Y_n|I = 1) - E(Y_o|I = 1) = X'(\beta_n - \beta_o) + (\sigma_{nc} - \sigma_{oc})\lambda_n \tag{24}$$

The total effect of the new technology can be determined by aggregating equation 24 over all the farms that have adopted the new technology.

Equations 22 and 23 provide point estimates of the expected value of Y. A measure of precision of these estimates is given by their standard errors (s.e.). The standard errors of the predicted values of $E(Y_n|I = 1)$ and $E(Y_o|I = 1)$ from the regressions are:

$$\begin{aligned} s.e.[E(Y_n|I{=}1)] &= \hat{\sigma}_n \sqrt{R(X_n^{*\prime}X_n^*)^{-1}R'} \\ s.e.[E(Y_o|I{=}1)] &= \hat{\sigma}_o \sqrt{R(X_o^{*\prime}X_o^*)^{-1}R'} \end{aligned} \tag{25}$$

where $\hat{\sigma}_i$ is the estimate of $\sigma_i$, $X_i^*$ includes X and $\lambda_i$ (i=o,n), and R is a row vector containing the values of X used for the prediction.

### Specification of Variables

Table 2 defines the variables used in the analysis. The dependent variables include the decision to adopt N testing (*NTEST*), and, on a per-acre basis, the N fertilizer application rate (*NFERT*), crop yield (*YIELD*), and net return (*RETURN*). Net return is calculated as the difference between the value of crop yield and the per-acre costs of all fertilizer and pesticide chemical inputs. Crop prices are the average annual prices received by farmers in their State (USDA, 1992). State-level average prices paid for fertilizer and major pesticides are from unpublished USDA statistics. For minor-use pesticides, national-level prices are used (DPRA Incorporated).

The factors affecting the endogenous variables include the N fertilizer-corn price ratio (*Pn/Pc*) and farm characteristics such as human capital, farm size, tenure status, risk aversion, and previous cropping history. Human capital

**Table 2 -- Description of variables used in statistical analysis**

| | |
|---|---|
| *Dependent variables*: | |
| NTEST | whether an N test was performed (1=yes; 0=no) |
| RETURN | net return -- revenue minus chemical input costs ($/acre) |
| YIELD | corn yield (bushels/acre) |
| NFERT | N fertilizer application (pounds/acre) |
| *Exogenous factors*: | |
| Pn/Pc | N fertilizer to corn price ratio (bushels of corn per pound of N) based on statewide average farm-level prices |
| REGULATE | proportion of cropland in county required to conduct N tests |
| PROJECT | sample field located in county with USDA water quality demonstration project or ASCS special project (1=yes; 0=no) |
| *Farm characteristics*: | |
| LHSCHOOL | farm operator did not complete high school (1=yes; 0=no) |
| HSCHOOL | farm operator just completed high school (1=yes; 0=no) |
| COLLEGE | farm operator has some college education (1=yes; 0=no) |
| EXPER | years the farmer has been operating a farm |
| SALE1 | gross annual farm sales < $100,000 (1=yes; 0=no) |
| SALE2 | gross annual sales between $100,000 and $250,000 (1=yes; 0=no) |
| SALE3 | gross annual sales > $250,000 (1=yes; 0=no) |
| OWNER | sample field owned by farm operator (1=owned; 0=rented) |
| CROPINS | farmer had insurance for crops grown in field (1=yes; 0=no) |
| IRRIG | field irrigated in past 3 years (1=yes; 0=no) |
| MANURE | manure applied to field or field pastured with livestock in past 3 years (1=yes; 0=no) |
| LEGUME | legume grown in field the previous season (1=yes; 0=no) |
| *Soil and weather variables*: | |
| SANDY | soil has sandy texture (1=yes; 0=no) |
| ORGMAT | organic matter of soil in top layer (percentage of weight) |
| pH | soil reaction (pH) |
| SLOPE | slope of field (percent) |
| T-FACTOR[1] | soil loss tolerance factor (acceptable level of annual soil loss -- 1 to 5 tons per acre). |
| SEASON | average number of frost-free days per year |
| RAIN | average annual precipitation (30-year average) |

[1] For formal definition of this variable, see Wischmeier and Smith.

consists of both the level of formal education (*LHSCHOOL*, *HSCHOOL*, and *COLLEGE*) and the years of farming experience (*EXPER*). Farm size is classified according to three levels of farm sales, which describe small, moderate, and large farms (*SALE1*, *SALE2*, and *SALE3*, respectively). Tenure status is a dummy variable indicating whether the sample field was owned by the farmer or not (*OWNER*). An imperfect indicator of risk aversion is whether the farmer had purchased crop insurance (*CROPINS*). Other things being equal, a more risk-averse farmer is assumed to be more likely to purchase crop insurance. A dummy variable indicated whether the field was irrigated (*IRRIG*). Previous cropping history includes whether the field had received an application of manure during the previous 3 years (*MANURE*) and whether the previous crop had been planted to either soybeans or alfalfa (*LEGUME*).

Also included in the set of farm characteristics are five soil quality variables and two weather variables. The quality of agricultural soils is derived from their effectiveness as a medium for providing essential nutrients and water for crop growth. Soil texture (the size of mineral particles) has a critical influence on water and nutrient retention, and is measured by a dummy variable for sandy soils (*SANDY*). Sandy soils have large particle size and, therefore, a low-water and low-nutrient retention ability. Cation exchange capacity (*pH*) measures the ability of the soil to bind and displace nutrient and pesticide molecules. The organic matter content (*ORGMAT*) of the soil influences plant growth by increasing water-holding capacity, improving soil tilth, and releasing some mineral nutrients (National Research Council, 1989). The other two soil quality variables are the slope (*SLOPE*) and the soil loss tolerances (*T-FACTOR*) of the field. The T-factor reflects soil depth as well as other factors (Wischmeier and Smith). Although these five variables measure different aspects of soil quality, they are not entirely independent of one another. Sandy soils, for example, tend to have lower organic matter content, lower pH values, and less soil depth. Also, organic matter can affect the pH level (National Research Council, 1978).

The two weather variables are the average annual rainfall and the average length of the growing season (number of freeze-free days). Rainfall data are available from the SCS for each sample point and are based on a 30-year precipitation record collected from 7,744 weather stations. The length of the growing season is based on the major land resource area (MLRA) in which the sample point fell. For each MLRA, a range of average freeze-free days over the MLRA is reported (USDA, 1981). The mid-point of this range is used as an estimate of the number of freeze-free days for the sample point.

In addition to prices and farm characteristics, two policy variables are included in the set of factors determining adoption (vector Z). A dummy variable (*PROJECT*) indicates whether or not a farm was located in a county that had a special USDA project providing educational, technical and/or financial assistance to promote the adoption of N testing and other technologies designed to reduce potential groundwater pollution from the use of agricultural chemicals. *REGULATE* gives the proportion of cropland in a county in which N testing is required under local statutes. Such statutes are in effect in several Nebraska counties where high concentrations of nitrates in groundwater have been detected. The regulations may require a farmer to conduct an N test and may limit fall applications of fertilizer, but do not restrict the amount of fertilizer applied (Williamson). By excluding the

*PROJECT* and *REGULATE* variables from the net return, fertilizer use, and crop yield functions, the model satisfies identification restrictions. These restrictions are based on the assumption that the policy variables only affect profit, demand, and supply through the farmer's decision to N-test or not, and not through other means.

## Results

### Factors Affecting N-Test Adoption

Estimates of a probit model of N test adoption are presented in table 3. The first column presents estimates using observations from all four Area Studies survey sites. The next three columns give estimates based on observations from Nebraska, Indiana, and Pennsylvania individually. There were an insufficient number of observations from the Mid-Columbia River Basin (Washington) to estimate the model for this site. For the models of individual watersheds, prices and weather variables were not included in the regressions since there was insufficient variability across observations within a watershed. The policy variables *REGULATE* and *PROJECT* only apply to certain areas where these policies are in effect.

Several "goodness of fit" measures are reported in the table. The $\chi^2$-statistic tests the overall explanatory power of the exogenous variables. The pseudo-$R^2$ (also called the likelihood index)[5] provides another relative measure of goodness of fit (McFadden). A third goodness of fit measure is the number of correct predictions. The probability of adoption for a farm with characteristics Z is given by $\Phi(Z'\gamma/\sigma)$, where $\Phi$ is the cumulative density function of the standard normal distribution. If the predicted probability of adoption is greater than 0.5, then the model is said to predict adoption ($\hat{I}$ = 1) for this farm. If the predicted probability is less than or equal to 0.5, then the model predicts nonadoption ($\hat{I}$ = 0). These measures suggest that the model explains the observed pattern of adoption in Nebraska much better than in the other areas. For Nebraska, 73 percent of the predictions for adoption and 75 percent of the predictions for nonadoption are correct. Poorer fits were obtained from the models using observations from Indiana and Pennsylvania (0 and 32 percent correct predictions for adoption, respectively).

One explanation for the better fit obtained for Nebraska may be due to the fact that the technology of N testing is well established in the Western States. As was pointed out above, relatively dry weather conditions tend to reduce soil N mobility, making it easier to predict the availability of soil N. In the humid regions of the Corn Belt, however, N test technology, such as the presidedress soil N test, is a more recent development. The failure of the probit model to explain adoption patterns in the Indiana and Pennsylvania sites may be because the technology has not been sufficiently developed to determine under what conditions it is likely to improve the efficiency of N management. Relative to Nebraska, farms in Indiana and Pennsylvania may be

---

[5] McFadden's pseudo $R^2$ is equal to $1-\ln L_u/\ln L_r$ where $\ln L_u$ is the log likelihood of the unconstrained model and $\ln L_r$ is the log likelihood of the model with all coefficients (other than the constant term) set to zero.

**Table 3 -- Factors affecting adoption of N testing (probit model)**

| Variable | All cases | | Nebraska | | Pennsylvania | | Indiana | |
|---|---|---|---|---|---|---|---|---|
| | coeff. | std. err. | Coeff. | Std. err. | Coeff. | Std. err. | Coeff. | Std. err. |
| Constant | -3.562 | 1.134 | -5.339 | 1.307 | -2.649 | 1.377 | -4.017 | 38.39 |
| Pn/Pc | 8.023 | 6.688 | -- | | -- | | -- | |
| REGULATE | 1.241 | 0.433 | 1.404 | 0.572 | -- | | -- | |
| PROJECT | 0.348 | 0.174 | 0.224 | 0.250 | 0.608 | 0.407 | -- | |
| HSCHOOL | 0.319 | 0.170 | 0.552 | 0.275 | -0.536 | 0.374 | 3.875 | 38.38 |
| COLLEGE | 0.554 | 0.176 | 1.059 | 0.288 | -0.039 | 0.498 | 3.728 | 38.38 |
| EXPER | -3.73E-3 | 3.67E-3 | 6.72E-3 | 6.25E-3 | -0.036 | 0.014 | -5.12E-3 | 5.50E-3 |
| SALE2 | -0.236 | 0.109 | -0.344 | 0.181 | -0.078 | 0.370 | -0.230 | 0.167 |
| SALE3 | 0.146 | 0.108 | 0.290 | 0.181 | 0.467 | 0.421 | -0.107 | 0.157 |
| OWNER | -0.167 | 0.094 | -0.429 | 0.160 | -0.438 | 0.348 | 0.052 | 0.139 |
| CROPINS | 0.324 | 0.092 | 0.324 | 0.142 | -4.148 | 68.78 | 0.343 | 0.154 |
| IRRIG | 0.814 | 0.132 | 0.836 | 0.172 | -3.512 | 120.7 | -3.767 | 233.1 |
| MANURE | 0.208 | 0.105 | 0.281 | 0.160 | 0.839 | 0.399 | -0.045 | 0.221 |
| LEGUME | -0.028 | 0.099 | -0.058 | 0.170 | 0.375 | 0.335 | -0.076 | 0.142 |
| SANDY | 0.249 | 0.145 | 0.486 | 0.214 | -4.268 | 77.41 | 0.189 | 0.474 |
| ORGMAT | 0.065 | 0.047 | 0.212 | 0.078 | -0.108 | 0.275 | -8.76E-3 | 7.60E-2 |
| pH | 0.116 | 0.079 | 0.375 | 0.151 | 0.401 | 0.247 | -0.164 | 0.143 |
| SLOPE | 9.54E-3 | 0.0102 | 0.021 | 0.017 | 4.83E-3 | 0.0316 | -0.041 | 0.025 |
| T-FACTOR | 0.0602 | 0.0519 | 0.041 | 0.093 | 0.0308 | 0.210 | 0.124 | 0.075 |
| SEASON | 2.71E-3 | 4.63E-3 | -- | | -- | | -- | |
| RAIN | -2.03E-4 | 9.983-3 | -- | | -- | | -- | |
| No. of cases | 1169 | | 449 | | 149 | | 566 | |
| $\Phi(Z'\gamma/\sigma)$[1] | 0.265 | | 0.506 | | 0.114 | | 0.0581 | |
| $\chi^2$ | 263.002 | | 170.14 | | 37.79 | | 36.03 | |
| Pseudo-$R^2$ | 0.186 | | 0.273 | | 0.280 | | 0.072 | |
| Correct predictions (percent): | | | | | | | | |
| Adopters | 49 | | 73 | | 32 | | 0 | |
| Nonadopters | 92 | | 75 | | 95 | | 100 | |

-- = variable not included in model

[1] Calculated at mean values of variables in Z.

located at an early point on a technology diffusion curve. Through longer exposure and experience, Nebraska farmers have determined many of the conditions where N testing is likely to be most profitable. The Nebraska observations are probably driving the results for the model using all observations as well.

To determine the effect of a change in an exogenous variable on the probability of adoption, the coefficients from a probit model must be multiplied by $\Phi(Z'\gamma/\sigma)$ (Maddala). For example, calculated at the mean values using the Nebraska observations, $\Phi(Z'\gamma/\sigma) = 0.506$. Irrigated farms in Nebraska were 42 percent more likely to adopt N testing than were unirrigated farms. Fields that had received a manure application were 14 percent more likely to be N tested compared with fields without manure.

The following discussion on N test adoption pertains to Nebraska, where the best fit of the adoption model was obtained. Mandatory regulations requiring N testing are (not surprisingly) highly correlated with adoption, while voluntary efforts through USDA education projects did not appear to significantly affect adoption rates.[6] Several characteristics of the field and farm are closely related to N test adoption. N test adoption occurred more frequently on irrigated fields and fields that received manure applications. Irrigated farms tend to use substantially more N fertilizer than unirrigated farms (figure 5), and N testing may have greater potential to reduce costs on these farms. One difficulty farmers face in properly crediting the N content of manure applications is uncertainty about the quality of manure being applied (Legg). N testing in these cases may help reduce this uncertainty by providing information concerning how much mineralized N is available in the soil.

More highly educated farmers, renters, and farmers with crop insurance were more likely to use N testing. Note that the coefficients on the education variables (*HSCHOOL* and *COLLEGE*) compare the probability of adoption with that of an individual with less than high school education. While formal education is significantly correlated with N test adoption, farming experience is not. This finding supports the notion that education and experience are not close human capital substitutes where adaptation to new technology is concerned (Schultz). One reason why renters may be more likely to adopt N testing is that this may be a tool for owners and renters to decide upon fertilizer application rates when these costs are shared. To the extent that purchasing crop insurance is a measure of risk aversion, the results support the hypothesis that more risk-averse farmers are more likely to adopt a risk-reducing input such as N testing (Feder; Robison and Barry).

There is a nonlinear relationship between farm size and technology adoption among Nebraska farms. The coefficients of *SALE2* and *SALE3* compare the

---

[6] In a companion paper (Bosch and others, 1993) the policy issues are discussed in detail. One finding was that while USDA educational efforts were not as effective as regulations in achieving high adoption rates, the USDA projects did have a significant educational effect. Farmers who participated in the projects appeared to make more use of the results of the N tests in their fertilizer management compared with farmers who did not participate.

adoption of N testing by moderate and large farms, respectively, with that of small farms. Moderately sized farms were less likely to adopt N testing, while there was no significant difference in adoption rates between small and large farms.

Several of the soil variables (soil texture (*SANDY*), organic matter content (*ORGMAT*), and soil pH) were statistically significant in explaining the pattern of N test adoption in Nebraska. It appears that farmers were more likely to employ N tests on soils with higher organic matter and on soils with sandy texture, even though a sandy texture is negatively correlated with organic matter content. Various forces may be interacting here. On the one hand, N is less mobile (and more easily predictable) in heavier soils with less leaching. At the same time, concerns over groundwater quality may be inducing or requiring farmers in sandy areas to adopt N testing as a way to reduce potential N losses. Several localities in Nebraska have adopted strict N fertilizer management regulations because of concerns over nitrate pollution of groundwater (Williamson).

**Switching Regression Model of N Use, Corn Yield, and Net Returns**

The switching regression model was used to assess the effect of N testing on N fertilizer use, crop yield, and net returns using only the observations in Nebraska. Pennsylvania and Indiana were not considered because the probit model of adoption did not fit the data well in these areas. Since the observations used in the switching regression model are from only one State, the price and weather variables were not included in the switching regression model due to limited observed variation in these variables within the State. Although the equations no longer contain economic parameters, they still can be considered to be the realized demand and supply functions reflecting the optimizing behavior of farmers.

Table 4 presents the estimates of the N fertilizer use, corn yield, and net return functions for adopters and nonadopters. The results support the hypothesis that the N use, yield, and net return functions differ between nonadopters and adopters. For nonadopters, N application on irrigated fields was 41 pounds/acre more than for unirrigated fields, but for N-test adopters, fertilizer application rates on irrigated and unirrigated farms were not statistically different. Furthermore, N-test adopters reduced commercial fertilizer N applications on fields that had received a manure application and on fields with higher levels of organic matter. Neither of these factors affected N application rates by nonadopters. Farmers who N tested and applied manure reduced their N application rates by 27 lb N/acre. Adopters also reduced their N fertilizer application by 9.5 lb N/acre for every 1-percent increase in organic matter. It appears that nonadopters failed to properly credit the N content in manure and soil organic matter.

For the corn yield functions, the estimated coefficients for the human capital variables (*HSCHOOL* and *COLLEGE*) were statistically different between N-test adopters and nonadopters. For nonadopters, human capital was associated with higher yields. Farmers with high school or some college education yielded, on average, 10 to 16 more bushels/acre than farmers with less than high school education. But these human capital variables did not explain yield differences among the group of adopters. This result may be a consequence of

**Table 4 -- Switching regression model of N test adoption**

| Variable | N fertilizer application (pounds N/acre) | | | | Corn yield (bushels/acre) | | | | Net return ($/acre) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Nonadopters | | Adopters | | Nonadopters | | Adopters | | Nonadopters | | Adopters | |
| Constant | 181.62 | (76.76) | 181.66 | (103.5) | 131.93 | (37.13) | 247.48 | (54.42) | 310.88 | (86.49) | 592.01 | (129.1) |
| REGULATE | -- | | -- | | -- | | -- | | -- | | -- | |
| PROJECT | -- | | -- | | -- | | -- | | -- | | -- | |
| HSCHOOL | 13.378 | (8.573) | 4.880 | (22.20) | 9.683 | (5.480) | -1.824 | (12.33) | 16.495 | (11.95) | -12.973 | (27.55) |
| COLLEGE | 11.382 | (10.94) | -21.855 | (22.69) | 16.346 | (7.535) | -2.669 | (12.52) | 35.567 | (17.70) | -14.623 | (27.91) |
| EXPER | -0.213 | (0.256) | 0.163 | (0.475) | -0.0087 | (0.139) | -0.228 | (0.268) | 0.186 | (0.335) | -0.441 | (0.642) |
| SALE2 | 18.548 | (7.943) | 9.644 | (13.23) | 6.640 | (3.701) | 3.335 | (7.211) | 7.484 | (8.564) | 5.238 | (16.98) |
| SALE3 | 3.869 | (7.366) | -26.131 | (13.76) | 1.796 | (4.464) | -3.553 | (7.434) | -2.124 | (9.879) | -13.743 | (17.92) |
| OWNER | 11.487 | (7.274) | 10.244 | (13.17) | -0.4085 | (3.922) | 11.976 | (7.734) | -2.535 | (9.262) | 25.244 | (17.90) |
| CROPINS | -11.382 | (7.476) | -8.932 | (10.85) | 2.772 | (3.522) | -0.131 | (6.114) | 9.711 | (8.360) | -4.314 | (14.51) |
| IRRIG | 40.891 | (12.16) | -6.383 | (12.85) | 59.722 | (6.471) | 37.045 | (7.269) | 123.70 | (15.09) | 73.670 | (17.22) |
| MANURE | -2.103 | (6.814) | -27.349 | (12.39) | 1.815 | (3.573) | -8.020 | (6.811) | 7.421 | (8.235) | -16.797 | (16.14) |
| LEGUME | -5.577 | (6.474) | -6.595 | (11.85) | 7.632 | (3.068) | 1.631 | (7.129) | 19.047 | (7.812) | 9.872 | (17.63) |
| SANDY | -6.045 | (11.18) | -17.377 | (15.26) | -13.944 | (5.052) | -26.77 | (8.502) | -40.063 | (11.58) | -63.804 | (20.34) |
| ORGMAT | -2.051 | (3.969) | -9.455 | (5.120) | 2.119 | (1.858) | -5.714 | (2.794) | 5.891 | (4.139) | -15.40 | (7.000) |
| pH | -15.567 | (8.424) | 7.974 | (10.28) | -12.970 | (4.512) | -13.41 | (6.273) | -33.904 | (10.81) | -35.67 | (15.32) |
| SLOPE | -1.213 | (0.963) | -1.510 | (1.374) | -1.030 | (0.446) | -0.857 | (0.604) | -2.654 | (1.099) | -1.848 | (1.474) |
| T-FACTOR | 3.170 | (8.545) | 1.272 | (11.32) | 4.503 | (1.581) | 2.279 | (3.655) | 8.181 | (3.693) | 7.466 | (8.496) |
| $\chi^2$ | 122.276 | | | | 215.748 | | | | 194.800 | | | |
| Variance | 39.935 | (2.751) | 70.736 | (5.089) | 20.042 | (1.320) | 36.785 | (2.224) | 47.162 | (2.743) | 94.066 | (5.708) |
| Covariance | 9.078 | (17.28) | -69.321 | (4.987) | -2.603 | (12.60) | -33.272 | (2.117) | 4.441 | (0.258) | -89.682 | (5.442) |

-- = variable not included in model.
Standard errors are in parentheses.

self-selection. In other words, farmers who choose to use the N test may have a higher level of (unobserved) management ability, regardless of their level of formal learning. The effects of human capital and irrigation were more pronounced on the net returns functions for nonadopters as well.

The differences observed in the behavior of N-test adopters and nonadopters may be due either to the effects of N testing or to systematic differences (observed or unobserved) between the two groups of farmers. The significance of unobserved effects is measured by the covariance terms. Three of the six covariance estimates (the three associated with the set of adopters, or $\sigma_{nc}$) are statistically significant, suggesting that sample selectivity is important. Failure to take into account sample selectivity would bias the estimates of the net return, supply, and input demand functions for the group of adopters.

**Economic and Environmental Effects of N Testing**

The switching regression method controls for differences in both observed and unobserved factors between adopters and nonadopters in evaluating the effects of technology adoption. Since the correlations between unobserved factors are important, it is essential to take sample selectivity into account when evaluating how N-test adoption has affected fertilizer use and yields. The predictions given by equations 22 to 24 show how farmers who are using N testing would have behaved if they had not adopted the technology. Sample selection bias is controlled by including the covariance terms in these equations.

Table 5 shows how the adoption of N testing changed N fertilizer use, corn yields, net returns, and potential N losses to the environment for different types of farms. Two types of cropping systems are considered. The first type involves farms that grow corn in rotation with legumes and apply manure (rotation and manuring system). The second type of cropping system is a continuous corn system without manure or rotations. The rotation and manuring system represents a set of cropping practices in which there is a high likelihood of significant carryover of organic N. About 18 percent of the sample were in this category. Twelve percent of the sample were in the continuous corn cropping system. This cropping system relies on inorganic commercial fertilizer N for nearly all N needs. The remaining farms (70 percent) either applied manure or grew legumes in rotation with corn, but not both.

In each cropping system, both irrigated and unirrigated farms are evaluated, and each of these in fields with favorable and unfavorable soil characteristics. The characteristics of unfavorable soils were determined by setting the soil texture dummy variable (*SANDY*) equal to 1 and taking the average values of the other soil variables. Unfavorable soils (*SANDY*=1) have 1.7 percent organic matter, a pH level of 6.7, and a *T-FACTOR* of 4.6 tons/year. Favorable soils (*SANDY*=0) have an organic matter content of 2.8 percent, a pH of 6.9, and a soil loss tolerance (*T-FACTOR*) of 4.8 tons/year. Other farm characteristics such as education, farm size, and tenure were set to representative values and left unchanged across the farm types (see footnote to table 5).

**Table 5 -- Economic and environmental implications of N testing**

| Cropping system[1] | N fertilizer application[2] (pounds N/acre) | | | Crop yield[2] (bushels/acre) | | | Net Returns ($/acre) | Residual N[3] (pounds N/acre) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $N_o$ | $N_n$ | $\Delta N$ | $Y_o$ | $Y_n$ | $\Delta Y$ | $\Delta R$ | $RN_o$ | $RN_n$ | $\Delta RN$ |
| *Rotation and manuring* | | | | | | | | | | |
| 1 Irrigated, good soil | 149 | 121 | -28 * | 150 | 141 | -9 | -12 | 44 | 23 | -21 |
| 2 Irrigated, poor soil | 146 | 120 | -26 * | 135 | 126 | -9 | -1 | 52 | 32 | -20 |
| 3 Unirrigated, good soil | 114 | 83 | -31 * | 88 | 82 | -6 | -21 | 52 | 26 | -26 |
| 4 Unirrigated, poor soil | 111 | 84 | -27 * | 74 | 68 | -6 | -8 | 60 | 36 | -24 |
| *Continuous corn* | | | | | | | | | | |
| 5 Irrigated, good soil | 158 | 144 | -14 | 140 | 142 | 2 | 7 | 60 | 45 | -15 |
| 6 Irrigated, poor soil | 156 | 144 | -12 | 126 | 128 | 2 | 18 | 68 | 54 | -14 |
| 7 Unirrigated, good soil | 123 | 104 | -19 * | 78 | 82 | 4 | -5 | 69 | 47 | -22 |
| 8 Unirrigated, poor soil | 121 | 105 | -16 * | 64 | 68 | 4 | 8 | 76 | 57 | -19 |

[1] In the rotation and manuring cropping system, the MANURE and LEGUME variables are set equal to 1. These variables are set to 0 in the continuous corn cropping system. "Good soil" means that soil texture dummy variable SANDY = 0, ORGMAT = 2.8, pH = 6.9, and T-FACTOR = 4.8. "Poor soil" means that soil texture dummy variable SANDY = 1, ORGMAT = 1.7, pH = 6.7, and T-FACTOR = 4.6. Other farm characteristics held constant at selected representative values: HSCHOOL=1; COLLEGE=0; SALE2=1; SALE3=0; OWNER=0; CROPINS=0; SLOPE=3; PROJECT=1; and REGULATE=0.

[2] $N_i$ and $Y_i$ are average N fertilizer application rates and crop yields before adoption (i=o) and after adoption (i=n) of N testing.
* = statistically significant difference in predicted means at the 10-percent significance level.

[3] $EN_i = N_i - 0.7*Y_i$. This assumes there are 0.7 pounds N/bushel corn (Meisinger). No statistical significance tests were conducted for EN.

The predicted changes in N fertilizer application rates, yields, and net profit were also evaluated for statistical significance. The standard error for the difference between the predicted means is the average of the two standard errors in equation 25. Under the null hypothesis that the predicted means are identical, the ratio of the predicted value to its standard error has a t-distribution. In table 5, statistical differences between the predicted means is indicated for the 10-percent level of significance.

N testing reduced N fertilizer application in all of the farm types, and the differences were statistically significant in six of the eight cases. N testing had the largest effect on N fertilizer use on fields that were more likely to have a higher level of N carryover from previous manure applications and legume crops (rotation and manuring cropping system). Average N fertilizer rates fell by 27 to 31 pounds N/acre on these farms compared with 12 to 19 pounds N/acre for continuous corn farms. The changes in N application rates were not statistically significant for irrigated, continuous corn farms.

Predicted changes in yield resulting from N test adoption varied from -9 bushels/acre to +4 bushels/acre. However, none of the yield differences were statistically significant. Farmers appear to have used N testing to identify fields in which residual carryover N was present rather than to determine whether their N applications were insufficient.

Estimated changes in net returns (also predicted from the switching regression equations) varied significantly across farm types, from -$21/acre to +$18/acre, although none of these values were statistically significant. N testing appears to be slightly more profitable on irrigated farms compared with unirrigated farms, which is consistent with the observed patterns of N test adoption. In other words, N testing appears to have been adopted in areas where it is the most profitable.

The overall effect of N testing on the efficiency of N fertilizer use is given by the change in N balance or "residual fertilizer N" ("ΔRN" in table 5). Residual N is defined as the difference between the quantity of commercial N fertilizer applied to the field and the amount of N removed in the grain at harvest. Assuming a steady state condition in the quantity of soil N, residual N will eventually be lost to surface runoff, leaching, or denitrification into the atmosphere (Meisinger and others). In Nebraska, much of the agricultural land is especially vulnerable to nitrate leaching (Huang and others), and residual fertilizer N may be contributing to high levels of nitrates observed in groundwater (Environmental Protection Agency). The change in residual fertilizer N is one measure of the environmental effect of N testing.

One measure of the reduction of residual fertilizer N is simply to take the average reduction of fertilizer application observed in the statistically significant cases, since changes in yields were not significant. A more conservative approach is also to consider the estimated yield effects, since some of these effects were negative (though not statistically significant). The second approach is used in table 5. The quantity of N in the harvested crop was estimated to be 0.7 pounds N/bushel corn (Meisinger). For example, for farm type 1, N testing changed N use by -28 pounds N/acre and yields by -9 bushels/acre. The N content of the change in yield is 6 pounds N/acre so the net change in potential N losses is -21 pounds N/acre. Note that these measures of the environmental effects of N testing consider only changes in commercial fertilizer N and not other sources of N such as manure and legume carryover. It assumes that manure applications and legume N carryover are not significantly different between adopters and nonadopters. Also, the environmental assessment only measures the change in the quantity of residual N. Determining the social cost of residual N is beyond the scope of this study.

N testing reduced the estimated residual N in all of the farm types considered. For fields in the rotation and manuring cropping system, N testing reduced residual fertilizer N by 20 to 26 pounds N/acre, or by 40 to 50 percent. For the fields in continuous corn, residual commercial fertilizer N fell by 14 to 19 pounds N/acre (although not statistically significant in all cases). By reducing the level of residual N, N testing can have a positive environmental effect since less N is available for potential losses through surface runoff, leaching to groundwater and denitrification. At the same time, farm productivity (measured by yields and net returns) was not negatively affected.

These results also suggest that there may not be a strong correlation between the private and environmental benefits of N testing. Although differences in net returns were not statistically significant, there was a tendency for the benefits from N testing, measured by changes in net returns, to be highest on irrigated farms compared with unirrigated farms, and on poorer soils. Environmental benefits measured by reductions in residual N, on the other hand, were higher for unirrigated farms compared with irrigated farms, with very little difference across soil types. Public policies that wish to maximize environmental benefits, therefore, might wish to target unirrigated farms. Note that although there are also social benefits from the adoption of N testing on irrigated farms, the private benefits might be sufficient to induce the voluntary adoption of N testing on many irrigated farms.

These findings on the effects on N testing are most relevant for agricultural conditions similar to those found in the Central Nebraska Basins. They should not be extrapolated to other areas such as the humid corn-producing regions in the Midwestern and Eastern parts of the United States. Adoption rates of N testing in the sampled areas of Indiana and Pennsylvania were not adequate to provide a meaningful econometric basis for an assessment of this technology in these areas. However, other studies previously cited (for example, Shortle and others) indicate N testing has some potential to reduce N losses and increase returns in the East and parts of the Midwest as well. Future research could investigate the effects of N testing in other regions of the country.

## Conclusions

Concern about nonpoint source pollution of water resources has resulted in a search for new technologies and farming practices that will reduce agriculture's contribution to pollution and enhance environmental quality. This report assesses the potential of better information (soil and tissue N testing) to improve N fertilizer management and reduce N losses to the environment.

A conceptual model indicated that the effects of N testing on N fertilizer use depend on farmers' attitudes toward risk and the nature of the production function. The model showed that more risk-averse farmers are more likely to reduce N applications in response to N testing due to the risk-reducing nature of an information input. For profit maximizers, N testing may increase, decrease, or leave the average level of N fertilizer application unchanged, depending on assumptions about the shape of the fertilizer response function. However, N testing can reduce potential N losses to the environment even in cases where average N use increases. If the N test indicates the need for greater N applications than would otherwise be applied, it is likely that much of the additional N will be used by the crop. When the test indicates that N applications can be reduced, much of the reduction would otherwise have been lost to runoff, leaching, or denitrification into the atmosphere.

The empirical analysis evaluated the adoption of N testing in corn production in four major watersheds in the United States. Farm-level data from the USDA Area Studies Survey were used for the analysis. Of the four areas studied, N testing has been most widely adopted in Nebraska. It was most likely to be used on irrigated farms, in fields that had previously received a manure application, by farmers with average or above-average education, and by farmers who purchased crop insurance. The adoption of N testing in the other watersheds was limited, possibly because the technology is newer in these areas.

The effect of adoption of N testing on N fertilizer use, corn yields, and net returns in Nebraska corn production were evaluated using an endogenous switching-regression model. The results indicated that N testing was particularly effective in improving the efficiency of N use by crops and reducing potential N losses to the environment on farms that applied manure to corn fields. On these farms, N testing reduced N fertilizer application rates while leaving crop yields unaffected. N testing was less effective in improving N efficiency in irrigated, continuous corn production systems that had not received manure application.

The results also suggested that private incentives may not be sufficient to achieve a socially optimal rate of N test adoption. The changes in net returns from the adoption of N testing were not large, nor was there a discernible correlation between the economic and environmental benefits from adoption. Market incentives alone may not be sufficient to encourage adoption of N testing in areas where reductions in excess N would be most significant. Public policies to encourage the adoption of N testing and related N management systems may be necessary to achieve significant improvements in environmental quality.

## References


Beegle, D., G. Roth, and R. Fox. "Nitrogen Soil Test for Corn in Pennsylvania." Agronomy Facts 17 (revised). University Park, PA: Cooperative Extension Service, Pennsylvania State University, no date.

Blackmer, A.M., T.F. Morris, and G.D. Binford. "Predicting N Fertilizer Needs for Corn in Humid Regions: Advances in Iowa." Chapter 5 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Bosch, D.J., Z.L. Cook, and K.O. Fuglie. "Voluntary Versus Mandatory Policies to Protect Water Quality: Adoption of Nitrogen Testing in Nebraska," mimeo, U.S. Department of Agriculture, Economic Research Service, 1993.

Bundy, L.G., M.A. Schmitt, and G.W. Randall. "Predicting N Fertilizer Needs for Corn in Humid Regions: Advances in the Upper Midwest." Chapter 6 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Cantor, P. "Health Effects of Agrichemicals in Groundwater: What Do We Know?" Agricultural Chemicals and Groundwater Protection: Emerging Management and Policy. Proceedings of a conference held in St. Paul, MN, October 22-23, 1988.

DPRA Incorporated. AGCHEMPRICE: Current U.S.A. Prices of Non-Fertilizer Agricultural Chemicals. Summary Edition. DPRA Inc., Manhattan, KS, April 1992.

Environmental Protection Agency. National Survey of Pesticides in Drinking Water Wells. Phase I Report, Environmental Protection Agency Report 570/9-90-015, November 1990.

Feder, G. "Pesticides, Information, and Pest Management Under Uncertainty," American Journal of Agricultural Economics. 61(1979):97-103.

Feder, G., R.E. Just, and D. Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey," Economic Development and Cultural Change. 33(1985):225-298.

Feder, G., and D.L. Umali. "The Adoption of Agricultural Innovations: A Review," Technological Forecasting and Social Change. 43(1993):215-239.

Feinerman, E., E.K. Choi, and S.R. Johnson. "Uncertainty and Split Nitrogen Application in Corn Production," American Journal of Agricultural Economics. 72(1990):975-984.

Fox, R.H., J.J. Meisinger, J.T. Sims, and W.P. Piekielek. "Predicting N Fertilizer Needs for Corn in Humid Regions: Advances in the Mid-Atlantic States." Chapter 4 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Hergert, G.W. "Status of Residual Nitrate-Nitrogen Soil Tests in the United States of America." Chapter 8 in J.R. Brown (ed.) Soil Testing: Sampling, Correlation, Calibration, and Interpretation. SSSA Special Publication Number 21. Madison, WI: Soil Science Society of America, Inc., 1987.

Hey, J.D. Uncertainty in Microeconomics. NY: New York University Press, 1979.

Hoeft, R.G., H.M. Brown, D. Mengel, D.J. Eckert, and M.L. Vitosh. "Predicting N Fertilizer Needs for Corn in Humid Regions: Advances in the Midwest." Chapter 7 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Huang, Wen-yuan, D. Westenbarger, and K. Mizer. "The Magnitude and Distribution of U.S. Cropland Vulnerable to Nitrate Leaching," Making Information Work. Conference Proceedings, January 18-23, 1992. Information Management Program, Center for Policy Research, National Governors Association, Washington, DC, 1992, pp. 177-196.

Lambert, D.K. "Risk Considerations in the Reduction of Nitrogen Fertilizer Use in Agricultural Production," Western Journal of Agricultural Economics. 15(1990):234-244.

Lee, L.F. "Unionism and Wage Rates: A Simultaneous Equation Model with Qualitative and Limited Dependent Variables," International Economic Review. 19(1978):415-33.

Legg, T.D. "Farm Level Effects of Environmental Policies Aimed at Nitrogen Management," unpublished Ph.D. thesis. St. Paul, MN: University of Minnesota, March 1991.

Maddala, G.S. Limited Dependent and Qualitative Variables in Econometrics. NY: Cambridge University Press, 1983.

Magdoff, F.R., W.E. Jokela, G.F. Griffin, and S.D. Klausner. "Predicting N Fertilizer Needs for Corn in Humid Regions: Advances in the Northeast." Chapter 3 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

McFadden, D. "The Measurement of Urban Travel Demand," Journal of Public Economics. 3(1974):303-328.

Meisinger, J.J. "Evaluating Plant-Available Nitrogen in Soil-Crop Systems." Chapter 26 in Nitrogen in Crop Production. ASA-CSSA-SSSA, Madison, WI, 1984, pp. 391-416.

Meisinger, J.J., F.R. Magdoff, and J.S. Schepers. "Predicting N Fertilizer Needs for Corn in Humid Regions: Underlying Principles." Chapter 2 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Meyer, J. "Two Moment Decision Models and Expected Utility Maximization," American Economic Review. 77(1987):421-430.

National Research Council. Nitrates: An Environmental Assessment. National Academy of Sciences, Washington, DC, 1978.

National Research Council. Alternative Agriculture. National Academy of Sciences, Washington, DC, 1989.

Office of Technology Assessment (U.S. Congress). Beneath the Bottom Line: Agricultural Approaches to Reduce Agrichemical Contamination of Groundwater. OTA-F-418, 1990.

Pitt, M. "Farm Level Fertilizer Demand in Java: A Meta-Production Function Approach," American Journal of Agricultural Economics. 65(1983):502-508.

Pratt, J.W. "Risk Aversion in the Small and in the Large," Econometrica. 32(1964):122-136.

Robison, L.J., and P.J. Barry. The Competitive Firm's Response to Risk. NY: Macmillan Publishing Company, 1987.

Rogers, E.M. Diffusion of Innovations, 3rd ed. NY: Free Press of Glencoe, 1983.

Schepers, J.S., T.M. Blackmer, and D.D. Francis. "Predicting N Fertilizer Needs for Corn in Humid Regions: Using Chlorophyll Meters." Chapter 8 in B.R. Bock and K.R. Kelley (eds.) Predicting N Fertilizer Needs for Corn in Humid Regions. Bulletin Y-226. Muscle Shoals, AL: National Fertilizer and Environmental Research Center, Tennessee Valley Authority, 1993.

Schultz, T.W. "The Value of the Ability to Deal with Disequilibria," Journal of Economic Literature. 13(1975):827-46.

Shortle, J.S., W.N. Musser, W.C. Huang, B. Roach, K. Kreahling, D. Beegle, and R.M. Fox. Economic and Environmental Potential of the Pre-sidedressing Soil Nitrate Test. Final Report to the Environmental Protection Agency. University Park, PA: Department of Agricultural Economics and Rural Sociology, Pennsylvania State University, 1993.

Tauer, L.W. "Risk Preferences of Dairy Farmers," North Central Journal of Agricultural Economics. 8(1986):7-15.

U.S. Department of Agriculture, Soil Conservation Service. Land Resource Regions and Major Land Resource Areas of the United States. AH-296, December 1981.

U.S. Department of Agriculture, National Agricultural Statistics Service. Agricultural Prices, 1991 Summary. June 1992.

Vroomen, H., and H. Taylor. Fertilizer Use and Price Statistics, 1960-91. SB-842, U.S. Department of Agriculture, Economic Research Service, November 1992.

Williamson, D. "Implementation of the Nebraska Nitrate Control Legislation," Nonpoint Pollution 1988: Policy, Economy, Management, and Appropriate Technology. American Water Resources Association, November 1988.

Willis, R.J., and S. Rosen. "Education and Self-Selection," Journal of Political Economy. 87(1979):S7-S36.

Wilson, P.N., and V.R. Eidman. "An Empirical Test of the Interval Approach for Estimating Risk Preferences," Western Journal of Agricultural Economics. 8(1983):170-182.

Wischmeier, W.H. and D.D. Smith. Predicting Rainfall Erosion Losses - A Guide to Conservation Planning. AH-537, U.S. Department of Agriculture, Soil Conservation Service, 1978.

**U.S. Department of Agriculture**
**Economic Research Service**
1301 New York Avenue, NW.
Washington, DC 20005-4788