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Precision farming : an economic and environmental analysis of within-field variability

Shivakumar B. Mahajanashetti

To the Graduate Council:

I am submitting herewith a dissertation written by Shivakumar B. Mahajanashetti entitled "Precision farming : an economic and environmental analysis of within-field variability." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Agricultural Economics.

Burton C. English, Major Professor

We have read this dissertation and recommend its acceptance:

Donald Tyler, Daryll Ray

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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and recommend its acceptance:

Darryll E. Ray

Donald Tyler

Accepted for the Council:

Associate Vice Chancellor and
Dean of the Graduate School

PRECISION FARMING: AN ECONOMIC AND ENVIRONMENTAL ANALYSIS OF WITHIN-FIELD VARIABILITY

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Shivakumar B. Mahajanashetti
May 1999

DEDICATION

This dissertation is dedicated to the memory
of my late parents

Mr. Basalingappa S. Mahajanashetti

and

Mrs. Shivagangavva B. Mahajanashetti

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ABSTRACT

This simulation study was conducted to investigate the role of within-field variability in realizing economic and environmental benefits from precision farming. The objectives of the study were to (i) illustrate *analytically* the influence of within-field variability on the economic outcomes of a given sampling intensity and therefore, the choice of the most economical sampling scheme, (ii) develop a method to determine the minimum spatial variability (distribution of land within a field with different production capabilities) needed so the additional returns from precision farming would at least cover the costs of using the technology, (iii) illustrate the role of weather expectations in precision farming, (iv) test the hypothesis that precision farming holds the promise of environmental benefits, and (v) examine policy options to motivate farmers to adopt precision farming, if the new technology is found to reduce environmental degradation.

The objectives were accomplished assuming that the farmers' main objective was profit maximization and that the technology was adopted by custom hiring the necessary services from the farm service sector.

The study created four hypothetical corn fields with different degrees of within-field variability on which nitrogen (N) was applied at variable rates based on soil sample tests. The results suggested, for each sampling intensity considered, that the more variability, the higher the returns above N costs with Variable Rate Technology (VRT) than with Uniform Rate Technology (URT). Further, it was indicated by the results that higher sampling intensity was economically optimal for the fields with higher variability, over a range of sampling costs considered.

Precision farming need not necessarily imply grid sampling. The technology could be used to apply inputs at spatially variable rates on different land types (classified, for example, according to soil series, slopes, landscape positions, etc.) with their own yield responses to applied inputs. Under such circumstances, economic feasibility of adopting VRT depends upon the existing land mix on the field. Given input and product prices, custom charges, and knowledge of yield response to applied inputs on two or more land types, the study developed a method to identify the required land proportions so the additional returns from VRT could at least cover custom charges. These proportions were referred to as *spatial break-even variability proportions*.

It is not just economic benefits that are claimed of precision farming. The new technology is also expected to benefit the environment by matching input application to plant and soil needs. The study investigated the potential of precision farming to reduce N loading into the environment. The Environmental Policy Integrated Climate (EPIC) crop growth model was used to estimate corn yield responses to applied N and predict total N losses on different soils under different rainfall scenarios.

The results indicated potential of the new technology to help reduce environmental degradation. The analysis suggested increasing importance of well-informed and accurate weather expectations under precision farming. In the majority of cases examined, farmers' decisions to adopt VRT meant economic losses when their rainfall expectations went wrong. Given the evidence of environmental benefits from being precise in input application, the study analyzed policy options to motivate farmers to adopt VRT. Subsidizing custom charges and restricting N use were the two options analyzed and found to help reduce N loss. The results showed totally different effects on production and farm incomes of input use restriction with and without VRT. With farmers having access to VRT, the fall in returns due to N restriction was much less than the fall that would have occurred with the same N use restriction without precision technology. Interestingly, when N use was restricted and farmers were forced to adopt VRT, production actually increased compared to the amount produced with URT under conditions of unconstrained N supply.

To sum up the findings of this study, the economic benefits from grid sampling depend upon the extent of variability; highly intensive sampling is beneficial for the fields with high variability. Farmers often have a broad idea of variability across the field based on characteristics like soil series, slope, soil depth and yield variability shown by yield monitors. Planned sampling needs to be guided by such prior experience.

The land mix on the field impacts the economic outcome of VRT. The method developed here helps find the minimum spatial variability needed on fields with two or more land types so the farmer can at least offset the custom charges with VRT adoption. The method is flexible and incorporates changing input and product prices as well as custom charges.

VRT holds environmental promise. However, a farmer's motive to adopt the technology is purely economic. As such, efforts are needed to make the technology attractive to farmer. Where the technology proves beneficial for the environment, government can subsidize custom charges to promote VRT adoption. Restricting input use could also promote technology adoption without much adverse effect on income and production. Farmers need to be more informed in formulating weather expectations under precision farming; the adverse effects on their economic interests due to wrong expectations can be more severe with VRT than with URT.

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Part 1: Introduction

Introduction

Precision farming, also known as precision agriculture, variable rate technology, site-specific farming or soil-specific farming, is gaining popularity. The phrase has been capturing the imagination of many concerned with the production of food, feed, and fiber (National Research Council, 1997). Several regional, national, and international conferences and seminars on precision agriculture testify to the growing interest in the subject.

The concept of precision farming is premised on the fact that farm fields are heterogeneous and hence, require differential treatment in management decisions. Several factors that are crucial for crop growth vary significantly across a given field, influencing the way in which crops respond to applied inputs (Carr et al., 1991; Fiez et al., 1994; Hannah et al., 1982; Karlen et al., 1990; Sawyer, 1994; Spratt and McIver, 1972). As such, treating the entire field as a homogeneous entity by applying production inputs at some uniform rate results in the input being under-applied in some sites within the field and over-applied in others. Such practice could lead to adverse economic and environmental consequences. Variable Rate Technology (VRT) takes a departure from the conventional 'one-fits-all' approach in farm management decisions. It identifies and measures the existing within-field variability and makes spatially variable input application prescriptions that match crop and soil needs.

Being precise in farming is not totally a new idea. The world's first farmers planted and fertilized each seed by hand. In doing so, they could achieve the largest possible precision (Morgan and Ess, 1997). Ancient agronomists practiced 'fish and hoe' agriculture according to which a dead fish was placed under a hill of corn to increase yield. When they were placing a bigger fish in poorer soils, they were in fact trying to be precise in planting (Rudolph and Searcy, 1994). Peasant farmers have practiced spatial management of crop inputs for centuries (Lowenberg-DeBoer and Swinton, 1995). However, in industrialized agriculture, farmers abandoned the idea of managing smaller-than-field size units (Morgan and Ess, 1997) due to economic considerations. Low crop product prices, high labor costs, low capital costs, and economies of scale prompted farmers to practice 'whole-field farming' (Lowenberg-DeBoer and Swinton, 1995). In recent years, mechanized agriculture has been witnessing renewed interest in managing smaller-than-field size units, due to the development and adoption of technologies that help farmers economically deal with within-field variability. It is this current trend towards precision in farming made possible through new technologies that is called 'precision farming'.

There is no single answer to the question, 'What operation on the field signifies the practice of precision farming?' Kitchen et al. (1996) write ".....any information gathering, management planning, or field operation that improves the understanding and management of soil and landscape resources so that cropping inputs or management practices (e.g., seed, fertilizers, herbicides, tillage etc.) are utilized more efficiently than with conventional 'one-fits-all' strategies could be called 'precision farming'."

Studies on precision farming have followed different approaches to gather information on within-field variability and achieving precision in input application. The methods adopted include grid sampling (Snyder, 1996), soil-type sampling (Carr et al., 1991); and, relying on soil mapping units delineated based on physical attributes like slope, fragipan depth, soil series and landscape position, and expected yield response to applied inputs (Barbosa, 1996).

The adoption of the above methods to assess within-field variability and apply inputs at spatially variable rates depends to a large degree on the economic benefits that the farmer expects to derive from the new technology. The advent of precision farming is hailed as a new era in agriculture that holds the promise of both economic and environmental benefits (National Research Council, 1997; Sawyer, 1994). However, in a market economy, the key to the acceptance of new technology is its profitability (Lowenberg-DeBoer and Swinton, 1995; Daberkow, 1997; Reetz and Fixen, 1995). Even if the perceived benefits of the technology are high, a negative impact on profitability may not be tolerated by production agriculture (Sawyer, 1994).

Economic Considerations

VRT with intensive soil sampling

Grid sampling furnishes information on how the soil environment varies across the field and this information becomes more accurate when the sampling intensity increases. With more accurate information, farmers can minimize the error in optimization of input use leading to higher returns over variable input costs. However, increased sampling intensity, at the same time, could entail a significant increase in the costs associated with sample collection and analysis. Therefore, what is needed is precise data balanced against the cost of sampling, when determining sampling density (Wollenhaupt and Wolkowski, 1994, described in Snyder, 1996). Note, however, that there can not be a single grid size that achieves this balance for each farm field with respect to each nutrient; it depends upon the nature and magnitude of variability of individual nutrients on the fields.

There are no studies in the literature on precision farming which illustrate, in a clear analytical framework, the influence of within-field variability on the economic outcomes of varying sampling intensities. Such an illustration should help farm managers understand the role of the degree of variability in realizing gains from grid sampling. Further, an illustration should also explain why the most economical sampling intensity may not be the same for all situations.

<u>VRT based on physical attributes and expected crop response to applied inputs</u>

The approach to precision application of inputs followed in some studies (Barbosa, 1996; English et al., 1998; Malzer et al., 1996; Roberts et al., 1999) was not based on soil test results. These studies, instead, prescribed spatially variable input applications based on certain physical attributes and crop yield responses to applied inputs observed on broadly identified land types. The simulation study by English et al. (1998) provided an economic criterion for adoption of precision agriculture based on such factors. The authors assumed Variable Rate Technology (VRT) adoption on a custom hire basis and nicely illustrated the role of spatial variability (relative shares of different land types on the field) in determining the profitability of technology adoption. Assuming a field setup with two kinds of land, poor and good, the authors calculated minimum and maximum limits on the share of poor land so the additional returns with

VRT could at least cover the custom charge. The two limits were referred to as *spatial break-even variability proportions*.

Since the purchase of VRT applicators results in large investment of capital, most farmers hire VRT services from the farm supply sector (Snyder, 1996; Swinton and Ahmed, 1996). The methodology provided by English et al. (1998) could help farmers aspiring to custom hire VRT services find out whether the land mix on their fields could provide positive returns to VRT. The scope of their methodology, however, was restricted to the analysis of a field situation with only two land types. Farm fields, more often than not, are characterized by more than two land types. As such, the scope of the methodology in English et al. (1998) needs expanding. Farmers with more diverse field situations need to know whether they can at least cover the additional cost incurred with VRT implementation, given the land mix on their fields. Also, for fields with given land types, knowledge of the pattern of spatial variability that generates maximum returns to VRT would be of interest. Such knowledge sheds light on the maximum economic potential of VRT for fields with particular lands.

Environmental Considerations

The claim has been made that precision farming has the potential to reduce environmental harm caused by excessive use of agricultural inputs, by applying them in the right quantities, at the right places, and at the right times to match crop and soil needs. However, most earlier studies ignored the effects of variable rate input application on the environment (Watkins et al., 1998; Lowenberg-DeBoer, 1996; Swinton and Ahmed, 1996). Losses of agricultural chemicals, especially nitrate nitrogen (NO_3-N), into ground water have been a continuing concern for society. If Site-Specific Management (SSM) practices are deemed beneficial for water quality, a public policy could evolve to reduce the cost of technology and encourage its increased adoption (Swinton and Ahmed, 1996). Therefore, more economic research needs to be conducted to test the hypothesis of environmental benefits associated with the new technology (Lowenberg-DeBoer and Swinton, 1995).

The literature on precision farming has also largely ignored one of the important sources of risk for VRT – temporal yield variability (Lowenberg-DeBoer and Swinton, 1995). Weather constitutes an important source of uncertainty in agriculture. Fluctuating weather patterns could cause large variations in crop yields and farm profits. If the crop management decisions do not fit the imminent weather conditions, farm operators could either incur losses or miss the higher economic gains. As such, farmers try to develop an expectation regarding the uncertain crop growing conditions and perform the field operations accordingly. While farmers benefit from correct weather expectations, they could suffer economic losses when the expectations go wrong. Given that the expectations regarding uncertain weather are likely to go wrong, it would be interesting to analyze and compare their economic consequences for precision farming and uniform rate application method. Such an analysis would indicate whether the economic potential of the new technology is more or less sensitive to weather conditions compared to the traditional method.

The present study is an attempt to address the above issues. The analysis is conducted assuming that the farmer's objective is profit maximization and that the farmer practices precision farming with VRT custom services hired from the farm supply sector if the expected additional returns from technology adoption at least equal the custom charges.

Objectives

The objectives of this simulation study were (i) to illustrate *analytically* how within-field variability influences the economic outcomes of alternative sampling intensities and, thereby, the choice of most economical sampling scheme, (ii) to illustrate the role of spatial break-even variability proportions in the fields with two or more land types, (iii) to illustrate the role of weather expectations in precision farming, (iv) to test the hypothesis that precision farming holds the promise of environmental benefits, and (v) to examine policy options to motivate farmers to adopt precision farming if the new technology is found to reduce environmental degradation.

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Part 2: Variable-Rate Technology: Within-Field Variability and Economic Gains from Grid Sampling

Introduction

Traditionally, farm fields are considered as homogeneous units by farm operators in their crop management decisions. It is, however, heterogeneity and not homogeneity that characterizes agricultural fields. On account of within-field variability, different sites in a given field exhibit different capabilities to utilize applied inputs and produce crop output (Carr et al., 1991; Hannah et al., 1982; Malzer et al., 1996; Sawyer, 1994).

Precision farming recognizes within-field variability and prescribes spatially variable input applications that match site-specific needs of heterogeneous farmlands. Since increased precision in input placement reduces over- and under-applications, it is claimed that Variable Rate Technology (VRT) promises both private economic benefits and common environmental benefits (Hayes et al., 1994; Fiez et al., 1994; Sawyer, 1994; Snyder, 1996). However, profitability is one favorable outcome desired by virtually all producers in a market economy (Lowenberg-DeBoer and Swinton, 1995). The voluntary adoption of VRT, therefore, is likely to be most dependent on private economic benefits (Daberkow, 1997; Sawyer, 1994).

Precision in farming is not an absolute concept. Different methods are adopted to collect information on within-field variability and increase precision in field operations. In the literature on precision farming, these methods include grid sampling (Snyder, 1996; Wibawa, 1991), soil type sampling (Carr et al., 1991; Wibawa, 1991); and, relying on soil mapping units delineated based on physical attributes like slope, fragipan depth, soil series and landscape position, and expected yield response to applied inputs (Barbosa, 1996; English et al., 1998; Malzer et al., 1996; Roberts et al., 1998).

The cost of grid soil sampling is a major share in VRT costs. The number of soil samples needed to represent the variability of the field has been a matter of discussion since at least the 1920's (Lindsley and Bauer, 1929 described in Franzen and Peck, 1995). The need for sampling to describe field variability has probably always had an economic bias (Peck, 1990). As the sampling intensity increases, the proportion of field variability revealed increases enabling the farmer to be more precise in input application and generate additional returns. However, increased sampling intensity could entail a significant increase in sampling costs even if the costs of handling and utilizing increased information largely remain the same. As such, the farmer seeking to switch from Uniform Rate Technology (URT) to VRT might be faced with the question, "Does grid sampling pay me, and if it does, what is the most economical sampling intensity for my field?"

A simulation study by Hibbard et al. (1993) compared the outcomes of using grids of different intensities for variable rate application of P (phosphorous) and K (potassium) fertilizers on a 40-acre corn field, with a target fertility buildup program. A soil test 'population' from 253 grids of 0.156 acre each on the field was the basis for the simulation of various fertility management scenarios including 0.625-ac, 2.5-ac and 10-ac grid sampling intensities. Comparing the net present value of net returns over a period of 24 years for each scenario of sampling intensity, the authors concluded that 10-ac grid sampling intensity generated higher returns than the other two scenarios. The authors noted that the results were driven by the costs of sampling schemes among other things.

Wibawa (1991) investigated the economic outcomes of wheat fertilization with different sampling intensities. The results showed that the smallest grid intensity considered in the analysis (49 feet) could produce significantly high yields, but led to the lowest returns on account of additional costs of sampling and testing.

The farmer, as a profit maximizer, seeks to optimize input use based on the perception of the Marginal Physical Productivity (MPP) of applied input. The perception of MPP depends upon the perceived yield response to applied input. With URT, the farmer determines the optimum input application based on the perception of field average MPP. When adopting VRT with grid sampling, the farmer gets information on the within-field variability, which enables him/her to perceive the spatially changing yield response functions. Thus, with VRT, the profit maximizing farmer switches from field average optimization to site specific optimization of applied input based on the perception of site specific MPP's.

Let us refer to the difference in the optimum returns above variable input costs between VRT and URT (excluding sampling and other costs associated with VRT) as the Net Return Difference (NRD), following English et al. (1998). Using the terminology of profit maximization, the question facing the farmer can be re-written as "Does grid sampling pay me, and if it does, what grid size assures me the largest surplus of NRD over the costs of sampling and VRT services?"

The answer to the above question is field-specific. Where the yield response to applied inputs is unchanging across the field, grid sampling only adds to costs; URT itself achieves the maximum possible precision in the optimization of applied input. When, on the other hand, several factors vary across the field causing variation in yield response (equivalently, variation in MPP of applied input), optimizing input use based on the perception of field average MPP could result in a large error. Under such circumstances, the information provided by grid sampling could help the farmer to be more precise in optimization and thereby increase the NRD. Therefore, a particular sampling scheme that increases net returns in some fields could jeopardize the farmers' economic interests if applied to others. Further, some farmers' fields could benefit from highly intensive sampling, while others could benefit from a less dense sampling.

No studies exist in the literature that illustrate, in a profit maximization framework, the influence of within-field variability on the economic outcomes of varying sampling intensities. The objective of this simulation study was to illustrate *analytically* how differences in within-field variability influence (i) the NRD associated with a given sampling intensity, and (ii) the economically optimal sampling intensity. This illustration should help farm managers understand the role of spatial variability in realizing gains from grid sampling and explain why the most economical sampling intensity may not be the same for all situations.

Methods

This section describes the procedure followed to accomplish the objectives of the study. Consider field-1 shown in Figure 1. It is a hypothetical corn field with a total area of 16X acres. The profit-maximizing farmer cultivating this field is contemplating site-specific optimization of applied N (N^a) using VRT. This, however, requires the farmer to understand site-specific corn yield response to N^a.

Field-1 with Varying Soil Test Levels* of N^r, V_1 and V_2 across the Grids

N^r_1, $V_{1,1}$ $V_{2,1}$	N^r_3, $V_{1,3}$ $V_{2,3}$	N^r_5, $V_{1,5}$ $V_{2,5}$	N^r_7, $V_{1,7}$ $V_{2,7}$
N^r_2, $V_{1,2}$ $V_{2,2}$	N^r_4, $V_{1,4}$ $V_{2,4}$	N^r_6, $V_{1,6}$ $V_{2,6}$	N^r_8, $V_{1,8}$ $V_{2,8}$
N^r_9, $V_{1,9}$ $V_{2,9}$	N^r_{11}, $V_{1,11}$ $V_{2,11}$	N^r_{13}, $V_{1,13}$ $V_{2,13}$	N^r_{15}, $V_{1,15}$ $V_{2,15}$
N^r_{10}, $V_{1,10}$ $V_{2,10}$	N^r_{12}, $V_{1,12}$ $V_{2,12}$	N^r_{14}, $V_{1,14}$ $V_{2,14}$	N^r_{16}, $V_{1,16}$ $V_{2,16}$

Field-2 Created from Test Levels for Field 1 (N^r and V_1 vary, but V_2 remains fixed at $\overline{V}_2$)

N^r_1, $V_{1,1}$ $\overline{V}_2$**	N^r_3, $V_{1,3}$ $\overline{V}_2$	N^r_5, $V_{1,5}$ $\overline{V}_2$	N^r_7, $V_{1,7}$ $\overline{V}_2$
N^r_2, $V_{1,2}$ $\overline{V}_2$	N^r_4, $V_{1,4}$ $\overline{V}_2$	N^r_6, $V_{1,6}$ $\overline{V}_2$	N^r_8, $V_{1,8}$ $\overline{V}_2$
N^r_9, $V_{1,9}$ $\overline{V}_2$	N^r_{11}, $V_{1,11}$ $\overline{V}_2$	N^r_{13}, $V_{1,13}$ $\overline{V}_2$	N^r_{15}, $V_{1,15}$ $\overline{V}_2$
N^r_{10}, $V_{1,10}$ $\overline{V}_2$	N^r_{12}, $V_{1,12}$ $\overline{V}_2$	N^r_{14}, $V_{1,14}$ $\overline{V}_2$	N^r_{16}, $V_{1,16}$ $\overline{V}_2$

Field-3 Created from Test Levels for Field 1 (N^r and V_2 vary, but V_1 remains fixed at $\overline{V}_1$)

N^r_1, $\overline{V}_1$ $V_{2,1}$	N^r_3, $\overline{V}_1$ $V_{2,3}$	N^r_5, $\overline{V}_1$ $V_{2,5}$	N^r_7, $\overline{V}_1$ $V_{2,7}$
N^r_2, $\overline{V}_1$ $V_{2,2}$	N^r_4, $\overline{V}_1$ $V_{2,4}$	N^r_6, $\overline{V}_1$ $V_{2,6}$	N^r_8, $\overline{V}_1$ $V_{2,8}$
N^r_9, $\overline{V}_1$ $V_{2,9}$	N^r_{11}, $\overline{V}_1$ $V_{2,11}$	N^r_{13}, $\overline{V}_1$ $V_{2,13}$	N^r_{15}, $\overline{V}_1$ $V_{2,15}$
N^r_{10}, $\overline{V}_1$ $V_{2,10}$	N^r_{12}, $\overline{V}_1$ $V_{2,12}$	N^r_{14}, $\overline{V}_1$ $V_{2,14}$	N^r_{16}, $\overline{V}_1$ $V_{2,16}$

Field-4 Created from Test Levels for Field 1 (N^r varies, but V_1 and V_2 remain fixed at $\overline{V}_1$ and $\overline{V}_2$)

N^r_1, $\overline{V}_1$ $\overline{V}_2$	N^r_3, $\overline{V}_1$ $\overline{V}_2$	N^r_5, $\overline{V}_1$ $\overline{V}_2$	N^r_7, $\overline{V}_1$ $\overline{V}_2$
N^r_2, $\overline{V}_1$ $\overline{V}_2$	N^r_4, $\overline{V}_1$ $\overline{V}_2$	N^r_6, $\overline{V}_1$ $\overline{V}_2$	N^r_8, $\overline{V}_1$ $\overline{V}_2$
N^r_9, $\overline{V}_1$ $\overline{V}_2$	N^r_{11}, $\overline{V}_1$ $\overline{V}_2$	N^r_{13}, $\overline{V}_1$ $\overline{V}_2$	N^r_{15}, $\overline{V}_1$ $\overline{V}_2$
N^r_{10}, $\overline{V}_1$ $\overline{V}_2$	N^r_{12}, $\overline{V}_1$ $\overline{V}_2$	N^r_{14}, $\overline{V}_1$ $\overline{V}_2$	N^r_{16}, $\overline{V}_1$ $\overline{V}_2$

Figure 1. Fields 1 – 4 with Soil Test Values for Each of the 16 X-Acre Grids

*For example, N^r_1, $V_{1,1}$ and $V_{2,1}$ refer, respectively, to N^r, V_1, and V_2 levels in grid-1; N^r_2, $V_{1,2}$ and $V_{2,2}$ refer, respectively, to N^r, V_1, and V_2 levels in grid-2 etc.

** $\overline{V}_1$ indicates the mean of V_1 values observed on field-1; $\overline{V}_2$ indicates the mean of V_2 values observed on field-1.

This analysis makes an important assumption that the farmer knows how corn yields respond to N^a depending upon the soil test levels of certain nutrients / characteristics, based on the information from published yield response experiments conducted on similar soils. Following Snyder et al. (1996), the following quadratic yield response to the sum of N^a and residual N (N^r) is assumed.

$$Y = \beta_0 + \beta_1 \times (N^a + N^r) + \beta_2 \times (N^a + N^r) \times (N^a + N^r) + \beta_3 \times V_1 + \beta_4 \times V_1 \times (N^a + N^r) + \beta_5 \times V_2 + \beta_6 \times V_2 \times (N^a + N^r) \quad [1]$$

Where, Y = estimated corn yield (bu/acre); N^a = applied N (lb/acre); N^r = residual N (lb/acre); V_1 and V_2 are two unspecified soil nutrients/characteristics that influence corn yields (units/acre); $\beta_0 \ldots \beta_6$ are the estimated parameters of the yield response function.

Fiez et al. (1994) defined total N supply available to the crop as the sum of preplant residual N, applied fertilizer N and postplant mineralized N. Following their definition, the positive intercept in Equation 1 (β_0) is attributed to mineralized N becoming available to the crop after planting. V_1 and V_2 in the equation could represent for example, residual phosphorous and sulfur, which have been shown to interact with N in affecting crop yields (Tweeten and Heady, 1962; Frank et al., 1990; Beaton and Fox, 1971).

The terms $\beta_2 \times (N^a + N^r) \times (N^a + N^r)$, $\beta_4 \times V_1 \times (N^a + N^r)$ and $\beta_6 \times V_2 \times (N^a + N^r)$ in Equation 1 imply that the MPP of N^a changes across the field depending upon the soil test levels of the three factors, N^r, V_1, and V_2. As such, the equation yields different yield response functions for N^a depending upon the soil test levels of these three factors.

According to the equation, the variation in other nutrients on the field is not significant enough to vary the MPP of N^a.

For adopting VRT, the operator of field-1 samples the field on an X-acre grid resulting in 16 grids. The soil samples are tested for the three nutrients/characteristics. Figure 1 shows soil test results for each of the sixteen grids. Based on the test levels, the farmer realizes that each X-acre grid has a different yield response function for N^a as described later.

Fields with Different Degrees of Within-Field Variability

Figure 1 shows three other 16 X-acre corn fields that have either no variability in V_1 or V_2 or the same variability in these nutrients/characteristics as found in field 1. The corn yield response to N^r, V_1 and V_2 on these fields is assumed to be the same as on field-1 (Equation 1). The four fields in Figure 1 represent four variability patterns.

Field-1 has different N^r, V_1 and V_2 levels in each of the 16 grids. By rearranging the terms in Equation 1, the yield response function for N^a from the jth grid on the field can be expressed as:

$$Y_j = (\beta_0 + \beta_1 \times N_j^r + \beta_2 \times N_j^r \times N_j^r + \beta_3 \times V_{1j} + \beta_4 \times V_{1j} \times N_j^r + \beta_5 \times V_{2j} + \beta_6 \times V_{2j} \times N_j^r)$$
$$+ (\beta_1 + 2 \times \beta_2 \times N_j^r + \beta_4 \times V_{1j} + \beta_6 \times V_{2j}) \times N^a + \beta_2 \times N^a \times N^a \qquad j = 1 \ldots 16 \qquad [2]$$

Where, Y_j = estimated corn yield (bu/acre) on the jth X-acre grid; N^a = applied N (lb/acre); N_j^r = residual N (lb/acre) on the jth grid; V_{1j} and V_{2j} are two residual nutrients/characteristics on the jth grid that influence corn yields (units/acre); $\beta_0 \ldots \beta_6$ are the estimated parameters of the yield response function.

Field-2 has varying N^r and V_1 levels across the grids that correspond to their levels across the grids of field-1. However, the level of V_2 remains constant at the mean level, $\overline{V}_2$, found in field-1, where $\overline{V}_2 = \frac{1}{16} \times \sum_{1}^{16} V_{2,j}$. The yield response to N^a from a jth X-acre grid can be expressed by re-writing Equation 1:

$$Y_j = (\beta_0 + \beta_1 \times N_j^r + \beta_2 \times N_j^r \times N_j^r + \beta_3 \times V_{1j} + \beta_4 \times V_{1j} \times N_j^r + \beta_5 \times \overline{V}_2 + \beta_6 \times \overline{V}_2 \times N_j^r)$$
$$+ (\beta_1 + 2 \times \beta_2 \times N_j^r + \beta_4 \times V_{1j} + \beta_6 \times \overline{V}_2) \times N^a + \beta_2 \times N^a \times N^a \qquad j = 1 \ldots 16 \qquad [3]$$

Field-3 has varying N^r and V_2 levels across the grids that correspond to their levels across the grids of field-1, while V_1 is constant at $\overline{V}_1$ obtained from field-1 such that $\overline{V}_1 = \frac{1}{16} \times \sum_{1}^{16} V_{1,j}$. The yield response to N^a from the jth grid can be expressed as:

$$Y_j = (\beta_0 + \beta_1 \times N_j^r + \beta_2 \times N_j^r \times N_j^r + \beta_3 \times \overline{V}_1 + \beta_4 \times \overline{V}_1 \times N_j^r + \beta_5 \times V_{2j} + \beta_6 \times V_{2j} \times N_j^r)$$
$$+ (\beta_1 + 2 \times \beta_2 \times N_j^r + \beta_4 \times \overline{V}_1 + \beta_6 \times V_{2j}) \times N^a + \beta_2 \times N^a \times N^a \qquad j = 1 \ldots 16 \qquad [4]$$

Field-4 is similar to the other fields except both V_1 and V_2 are held constant at their field-1 means of $\overline{V}_1$ and $\overline{V}_2$. The yield response from the jth grid can be expressed as:

$$Y_j = (\beta_0 + \beta_1 \times N_j^r + \beta_2 \times N_j^r \times N_j^r + \beta_3 \times \overline{V}_1 + \beta_4 \times \overline{V}_1 \times N_j^r + \beta_5 \times \overline{V}_2 + \beta_6 \times \overline{V}_2 \times N_j^r)$$
$$+ (\beta_1 + 2 \times \beta_2 \times N_j^r + \beta_4 \times \overline{V}_1 + \beta_6 \times \overline{V}_2) \times N^a + \beta_2 \times N^a \times N^a \qquad j = 1 \ldots 16 \qquad [5]$$

As Equations 2 – 5 show, the MPP of N^a varies across the grids on each field; the variation is caused by the varying levels of N^r, V_1 and V_2 on field-1, N^r and V_1 on field-2, N^r and V_2 on field-3, and only N^r on field-4. The farmer seeking to optimize N^a with

URT, or VRT with larger than X-acre grids, does not use this precise information on grid-to-grid variation and relies on the perception of an average MPP. As a result, he/she commits an error when optimizing N^a. Since the perception of average MPP is the result of relying on average values of N^r, V_1 and V_2, the error in optimization is in fact related to the error committed in understanding the levels of these three nutrients/characteristics. Therefore, for comparing and contrasting the economic outcomes of URT and VRT, this analysis differentiates the nutrient variability pattern on the four fields according to the number of MPP influencing factors that vary across the field. Specifically, field-1 represents high nutrient variability; field-4 represents low nutrient variability; and the other two fields represent moderate variability.

Sampling Intensities

When following uniform rate input application, the farmer relies on the soil test levels obtained from the analysis of a single composite soil sample representing the entire field. When following variable rate input application, he/she grid samples the field at a certain density and treats each grid according to the respective soil test levels revealed.

The soil test results available on an X-acre grid for the four fields can be used to simulate different sampling intensities (Hibbard et al., 1993). For example, for simulating a 2X-acre grid, the soil test levels can be averaged for grid-1 and 2; grid-3 and 4; grid-5 and 6 and so on. The average values can be taken as representative of the respective 2X-acre grids. Similarly, for simulating a 4X-acre grid, the test levels can be averaged for grid-1, 2, 3, and 4; grid-5, 6, 7, and 8 and so on. This procedure can be applied to each of the three nutrients, N^r, V_1 and V_2 on each of the four fields. For simulating uniform rate application, soil test levels for all 16 of the X-acre grids can be averaged.

Economically Optimum Input Application and Returns

Uniform Rate Application Method

When applying N with URT, the farmer collects a single composite soil sample and gets it tested for N^r, V_1 and V_2, which reveals $\overline{V}_1$, $\overline{V}_2$, and $\overline{N}^r$, where

$\overline{N}^r = \frac{1}{16} \times \sum_1^{16} N_j^r$. Under this method, the farmer is not concerned with the site-specific corn yield response function for N^a given by Equations 2 – 5. Instead, he/she perceives the following field average response function for N^a, and seeks to optimize N application accordingly:

$$\overline{Y} = (\beta_0 + \beta_1 \times \overline{N}^r + \beta_2 \times \overline{N}^r \times \overline{N}^r + \beta_3 \times \overline{V}_1 + \beta_4 \times \overline{V}_1 \times \overline{N}^r + \beta_5 \times \overline{V}_2 + \beta_6 \times \overline{V}_2 \times \overline{N}^r) + (\beta_1 + 2 \times \beta_2 \times \overline{N}^r + \beta_4 \times \overline{V}_1 + \beta_6 \times \overline{V}_2) \times \overline{N}^a + \beta_2 \times \overline{N}^a \times \overline{N}^a \qquad [6]$$

Where, $\overline{Y}$ = estimated field average corn yield (bu/acre); $\overline{N}^a$ = field average N application rate (lb/acre); and the other terms are as described above.

Given corn and N prices (P_C and P_N), the profit maximizing farmer following URT determines the optimum field average N application ($\dot{\overline{N}}^a$) based on his/her perception of the MPP of N^a. The optimality condition is determined from Equation 6, by taking the first derivative with respect to $\overline{N}^a$, setting it equal to the ratio of P_N to P_C, and then solving the resulting equation for $\overline{N}^a$. Specifically, solving the following optimality condition yields the optimum field average N application rate:

$$\dot{\overline{N}}^{*} = \frac{{}^{P_N}\!/\!_{P_C} - \left(\beta_1 + 2\times\beta_2\times\overline{N}_r + \beta_4\times\overline{V}_1 + \beta_6\times\overline{V}_2\right)}{2\times\beta_2} \qquad [7]$$

Since all the four fields have the same $\overline{V}_1$, $\overline{V}_2$, $\overline{N}^r$ and response functions, the solution given by Equation 7 applies to them all. In other words, under uniform rate application, all four fields receive the same amount of N per acre, $\dot{\overline{N}}^{*}$. The total optimum returns above N costs from any of the four field under uniform rate application method, denoted as $\dot{R}^{URA}$, can be calculated as:

$\dot{R}^{URA} = X\times(P_C \times \sum_{1}^{16} Y_j$ - $16\times P_N \times \dot{\overline{N}}^{*})$. Since the units of Y_j and $\dot{\overline{N}}^{*}$ are both expressed on per acre basis, but the area of each of the 16 grids is X-acres, the quantity $(P_C \times \sum_{1}^{16} Y_j$ - $P_N \times 16\times \dot{\overline{N}}^{*})$ is multiplied by X so we get $\dot{R}^{URA}$ for the actual field area.

Variable Rate Application Method

Suppose these fields are instead managed under variable rate N application. Assume for illustration purposes that variable rate application is based on soil test results obtained on a 4X-acre grid. Each of the four fields, then, contains four 4X-acre grids, say, G_1, G_2, G_3, and G_4. Consider G_1 on field-1. Soil test levels for field-1 available on an X-acre grid are used to calculate the test levels for G_1. Specifically, the level of N^r in G_1, denoted as $N^r_{G_1}$, is calculated as $N^r_{G_1} = \frac{1}{4}\times\sum_{1}^{4} N^r_j$; level of V_1 as $V_{1,G_1} = \frac{1}{4}\times \sum_{1}^{4} V_{1,j}$; and the level of V_2 as $V_{2,G_1} = \frac{1}{4}\times\sum_{1}^{4} V_{2,j}$.

The farmer now perceives that the response function for grid G_1 takes the form (obtained by re-writing Equation 1):

$$Y_{G_1} = (\beta_0 + \beta_1 \times N^r_{G_1} + \beta_2 \times N^r_{G_1} \times N^r_{G_1} + \beta_3 \times V_{1,G_1} + \beta_4 \times V_{1,G_1} \times N^r_{G_1} + \beta_5 \times V_{2,G_1} +$$

$$\beta_6 \times V_{2,G_1} \times N^r_{G_1}) + (\beta_1 + 2 \times \beta_2 \times N^r_{G_1} + \beta_4 \times V_{1,G_1} + \beta_6 \times V_{2,G_1}) \times N^a_{G_1} +$$

$$\beta_2 \times N^a_{G_1} \times N^a_{G_1} \quad [8]$$

Where, Y_{G_1} = estimated average corn yield for grid G_1 (bu/acre); $N^r_{G_1}$ = N^r in grid G_1 (lb/acre); V_{1,G_1} = V_1 in the grid (units/acre); V_{2,G_1} = V_2 in the grid (units/acre); and $N^a_{G_1}$ = average N application rate for grid G_1.

The following equation gives the optimum grid average applied N ($\dot{N}^a_{G_1}$):

$$\dot{N}^a_{G_1} = \frac{P_N/P_C - (\beta_1 + 2 \times \beta_2 \times N^r_{G_1} + \beta_4 \times V_{1,G_1} + \beta_6 \times V_{2,G_1})}{2 \times \beta_2} \quad [9]$$

The farmer applies N at the rate of $\dot{N}^a_{G_1}$ (lb/acre) to the 4X-acre grid, G_1. The four smaller X-acre grids contained in G_1 have their own levels of V_1, V_2, and N_r and therefore, contribute differently to the total production from G_1. The total optimum returns above N costs from the 4X-acre grid G_1 under variable rate application method may be denoted as $\dot{R}^{VRA}_{G_1}$ and calculated as:

$$\dot{R}^{VRA}_{G_1} = X \times (P_C \times \sum_{1}^{4} Y_j - 4 \times P_N \times \dot{N}^a_{G_1}).$$

Recall that field-1 has three other 4X-acre grids, namely G_2, G_3, and G_4. Similar procedure can be used to calculate optimum returns from them. Adding the optimum returns from G_1, G_2, G_3, and G_4 yields the total optimum returns from field-1 under variable rate application with 4X-acre grid sampling. We can now calculate NRD by subtracting $\dot{R}^{URA}$ from $(\dot{R}_{G_1}^{VRA} + \dot{R}_{G_2}^{VRA} + \dot{R}_{G_3}^{VRA} + \dot{R}_{G_4}^{VRA})$.

This procedure can be applied to the other three fields. Further, in addition to the 4X-acre grid sampling described above, several other sampling intensities can be simulated and NRD's for the four fields compared and contrasted. The relevant information ignored in optimizing input use with URT is different for each field. The comparison of NRD's, therefore, illustrates the economic significance of reducing/eliminating varying levels of information loss resulting from URT.

Application to a Hypothetical Field

The methods explained in the previous section were applied to a hypothetical 90-acre corn field. The yield response function (Equation 1) was represented as

$$Y = 25 + 0.75 \times (N^a + N^r) - 0.0033 \times (N^a + N^r) \times (N^a + N^r) + 5 \times V_1 + 0.04 \times (N^a + N^r) \times V_1 + 6 \times V_2 + 0.06 \times (N^a + N^r) \times V_2 \quad [10]$$

The field was grid sampled on 0.625-acre grid, which resulted in a total of 144 grids and soil test levels of N^r, V_1 and V_2 for each grid. The soil test values for each of the 144 grids were generated using a random number generator.[1] N^r values (lb/acre) were generated such that $0 < N^r \leq 100$ and V_1 and V_2 values (units/acre) were generated such that $0 < V_1 \leq 10$ and $0 < V_2 \leq 10$. The analysis assumed P_C = \$2.79/bu, a five-year average corn price for 1993-1997 and P_N = \$0.26/lb, a five-year average N price over the

[1] This study assumes the value for each grid is independent from other grids in the field.

same period, with urea as the source of N (Tennessee Department of Agriculture /Tennessee Agricultural Statistical Service).

Three additional fields were created using the soil test values generated for the hypothetical 90-acre corn field described above following the procedures explained in methods section. To examine the effect of variability on the economically optimal sampling intensity, different sampling intensities including 10-acre, 5-acre, 2.5-acre, and 1.25-acre grids were simulated using the randomly generated soil test levels for the 0.625-acre grids.

Results

Table 1 presents optimum returns above N costs along with the Net Return Differences (NRD's) for each sampling intensity in relation to the pattern of variability. NRD was smallest for the low variability field (i.e., when only N^r varied across the field), largest for the high variability field (i.e., when N^r, V_1 and V_2 varied) and in between for the two fields with moderate variability (i.e., when N^r and either of V_1 and V_2 varied). This was true of any sampling intensity. As an example, for 10-acre grid sampling, NRD was \$22.64, \$36.28, \$92.16, and \$92.49 for the fields representing low variability, moderate variability-1, moderate variability-2, and high variability respectively. With 0.625-acre grids, the respective NRD's were \$736.87, \$1066.67, \$1208.75, and \$1481.62. This implied that URT on high variability field overlooked a large amount of information necessary for the precise understanding of the MPP, causing a large error in optimizing N^a. When VRT was adopted on the field, the error was corrected, which resulted in a large NRD. The opposite phenomenon happened in the case of low variability field.

Table 1. Net Return Differences (NRD) Associated with Various Sampling Intensities for Different Degrees of Within-Field Variability

Sampling Intensity	No. of Samples	Degrees of Variability Characterizing Fields							
		Low Variability*		Moderate Variability-1		Moderate Variability-2		High Variability	
		Optimum Returns†	NRD‡	Optimum Returns	NRD	Optimum Returns	NRD	Optimum Returns	NRD
		($)							
Single Composite Sample	1	48193.11	-	48105.19	-	48259.87	-	48174.93	-
10-Acre Grids	9	48215.75	22.64	48141.47	36.28	48352.03	92.16	48267.42	92.49
5-Acre Grids	18	48237.51	44.40	48172.79	67.60	48378.24	118.37	48300.95	126.02
2.5-Acre Grids	36	48391.03	197.92	48406.31	301.12	48524.80	264.93	48488.27	313.34
1.25-Acre Grids	72	48621.28	428.17	48706.74	601.55	48831.55	571.68	48861.48	686.55
0.625-Acre Grids	144	48929.98	736.87	49171.86	1066.67	49468.62	1208.75	49656.55	1481.62

*On the field showing low variability, only N^r levels vary and V_1 and V_2 levels remain constant at the mean levels; on the field showing moderate variability-1, N^r and V_1 vary with V_2 remaining constant; on the field with moderate variability-2, only N^r and V_2 vary; and, on the high variability field, all the three nutrients, viz., N^r, V_1 as well V_2 vary.

† Returns above N costs.

‡ Optimum returns above N costs under VRT with respective sampling intensities minus optimum returns under URT with a single composite soil sample.

This analysis compared and contrasted VRT outcomes according to the number of the nutrients/characteristics that varied across the field. That is, VRT outcomes when N^r, V_1 and V_2 all varied on the field (high variability) were compared with the outcomes when only one of them (low variability) or two of them (moderate variability) varied. However, on each of the two moderate variability fields, two nutrients/characteristics varied. The study did not compare the NRD's on these two fields since it would not reflect the degree of nutrient variability as per the definition followed in the analysis.

The surplus of NRD over the sampling and other VRT costs represents a net economic gain to the farmer from VRT. Thus, given these costs, the magnitude of NRD is of prime concern for the farmer contemplating VRT adoption. As per the results, the higher nutrient variability, the higher the NRD and, therefore, the higher the prospects of profits from VRT.

Table 1 also reveals that NRD kept rising as the sampling intensity increased for each of the four fields. Increasing sampling intensity provided more precise information on spatial variability of nutrients. This, in turn, increased the accuracy of input application leading to higher optimum returns and NRD. However, the higher NRD's were associated with larger number of soil samples analyzed, implying higher costs.

Table 2 shows how the degree of within-field variability influenced the optimum grid size, given the unit sampling cost. The optimum grid size was defined as the one that would enable the farmer to enjoy the largest surplus of NRD over the total costs of sample collection and analysis. This concept assumed that the VRT costs other than the costs of sample collection and analysis were invariant with respect to sampling intensity.

Table 2: Optimum Grid Sizes for Different Degrees of Within-Field Variability

Costs per Soil Sample*	Low Within - Field Variability		Moderate Within – Field Variability-1		Moderate Within – Field Variability-2		High Within – Field Variability	
	Optimum Grid Size	Optimum Returns†	Optimum Grid Size	Optimum Returns	Optimum Grid Size	Optimum Returns	Optimum Grid Size	Optimum Returns
($)		($)		($)		($)		($)
5	1.25-acre	68.17	0.625-acre	346.67	0.625-acre	488.75	0.625-acre	761.62
6	-	-	0.625-acre	202.67	0.625-acre	344.75	0.625-acre	617.62
7	-	-	1.25-acre	89.55	0.625-acre	184.75	0.625-acre	457.62
8	-	-	1.25-acre	25.55	0.625-acre	56.75	0.625-acre	329.62
9	-	-	-	-	10-acre	11.16	0.625-acre	185.62

*Refers only to the cost of collecting and analyzing a sample; other VRT costs are assumed to be constant for all sampling intensities.

† Refers to the surplus of NRD over total costs of collecting and analyzing soil samples.

The cost of a soil sample ranges from $4 to$18 depending upon the type of analysis and the number of nutrients tested (Snyder, 1996). For illustration purposes, the cost of collecting and analyzing a sample was varied over a small range from $5 to $9 per sample in $1 increments. As indicated by the results, given the sampling costs, the optimum grid size either remained the same or decreased (or optimum sampling intensity either remained the same or increased) as the variability increased. The results implied that when a high degree of within-field variability existed, most intensive sampling (0.625-acre grids) was the most economical over all sampling costs.

Conclusion

This study provided an analytical illustration of the role of within-field nutrient variability in precision farming using a profit maximization framework. The findings of the study suggested two important things. First, when several factors that impact the MPP of an applied input vary across the field, the information loss with URT or alternatively, the information gain from VRT is large. Under such circumstances, the NRD is large and therefore, the prospects of economic gains to the farmer from VRT adoption are high. On the other hand, when the variability on the field is low and the information loss with URT or gain from VRT is not much, the NRD is low implying low prospects of economic gains from VRT.

Secondly, the results suggested in general that higher sampling intensity was economically optimal for the fields with higher variability. For example, 0.625-acre grids were economically optimal over the entire range of sampling costs on the field with high variability.

Often, farmers have a broad idea of variability across the field, which can help them assess the feasibility of going for VRT. For example, knowledge of varying field characteristics like soil series, soil depth and slope and the information on spatial yield distribution obtained from yield monitors can help farmers make some guess work about the variability. Such farmers can learn from this study how within-field variability matters economically for their planned implementation of VRT.

Some caution is needed in interpreting the results of this simulation study. Using the yield response function for the sum of preplant residual N (N^r) and applied N (N^a) in the study is based on the assumption that preplant soil test levels fairly indicate the availability of the nutrient to the plants. N being highly volatile in the soil, this assumption is reasonable only with respect to the areas where leaching is not a major problem.

The results should not be interpreted to mean that 0.625-acre grids could be profitable for the farmers. They need to be interpreted in relative terms. The results only imply that when within-field variability is high, a high sampling intensity can be justified if the variable element being measured has an impact on yields. In fact, when the response function assumed in the study is changed or N^r, V_1 and V_2 are varied in different magnitudes across the field, the optimal grid sizes for the fields could change; 0.625-acre grids could prove optimal for none of the fields. Similarly, when the unit cost of sampling increases much above $9, 0.625-acre grids might turn out to be uneconomical on any of the study fields.

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Part 3: Spatial Break-Even Variability: An Economic Perspective of Precision Farming

Introduction

Agricultural fields consist of numerous areas that differ from one another with respect to the factors that condition crop growth (Carr et al., 1991; Hannah et al., 1982; Hibbard et al., 1993; Malzer et al., 1996; Sawyer, 1994; Spratt and McIver, 1972). As a result, the traditional way of looking at the entire field as a homogeneous unit in crop management decisions results in under-and over-application of inputs across the field.

Precision farming or site-specific farming - a newly emerging technology - recognizes that farm fields are rather heterogeneous units. It identifies, measures, and suitably treats the existing within-field variability. Though the term 'precision farming' is relatively new, the concept of precision in farming is not. Peasant farmers have practiced spatial management of crop inputs for centuries (Lowenberg-DeBoer and Swinton, 1995). However, in industrialized agriculture, farmers abandoned the idea of managing smaller-than-field size units (Morgan and Ess, 1997) due to economic considerations. Low crop product prices, high labor costs, low capital costs, and economies of scale prompted farmers to practice 'whole-field farming' (Lowenberg-DeBoer and Swinton, 1995). In recent years, mechanized agriculture has been witnessing renewed interest in managing smaller-than-field size units, due to the development and adoption of technologies that help farmers economically deal with within-field variability. It is this current trend towards precision in farming made possible through new technologies that is called 'precision farming'.

The two important benefits claimed of precision farming include increased profits to farmers and reduced environmental harm as a result of more precise placement of inputs (Kitchen et al., 1996; Koo and Williams, 1996; Sawyer, 1994; Watkins et al., 1998). The key, however, to the acceptance of site-specific farming is the profitability of the technology (Daberkow, 1997; Reetz and Fixen, 1995). Even if the perceived benefits of the technology are strong, a negative impact on profitability may not be tolerated by production agriculture (Sawyer, 1994).

The presence of variability in soil and field characteristics is the key to economic viability of precision farming (English et al., 1998; Forcella 1993; Hayes et al., 1994; Snyder, 1996). Use of precision farming technology on a field that is largely uniform only adds to costs. Thus, from a purely economic standpoint, the factors that drive the adoption of precision farming technology are 'spatial variability (distribution in the field, of lands with different production capabilities) and the magnitude of spatial yield differences' (English et al., 1998). Forcella (1993) showed how economic outcomes of nitrogen (N) application differed among several hypothetical corn fields consisting of two soil types depending upon the degree of spatial variability. The study revealed that economic benefits from managing soils by prescription increased with increasing spatial variability. The costs of precision technology were not explicitly considered in the analysis.

A simulation study by English et al. (1998) analyzed the role of spatial variability and spatial yield differences with emphasis on minimum spatial variability required for the adoption of custom hired Variable Rate Technology (VRT). The authors considered a hypothetical corn field consisting of two kinds of land, poor and good, with different yield response functions for applied N. The farmer was assumed to optimize N application based on the knowledge of two individual response functions, under variable rate application method. With Uniform Rate Technology (URT), optimization of N application was based on an average response function. The parameters of the average response function were weighted averages of the parameters of the two individual response functions, with proportions of the two land types in the field as weights. The Net Return Difference (NRD) that referred to the difference in optimum returns over variable costs between the two application methods was calculated for various proportions of the field in poor land. The authors located the minimum and maximum proportions of the field in poor land that bounded the proportions promising positive returns to VRT, i.e., the region where NRD was greater than the custom charges (C). The two limits of the region were referred to as *spatial break-even variability proportions*, since they enabled the farmer to just break even using the technology (NRD = C). When the proportion of the poor land on the field fell outside the range bounded by the two break-even variability proportions, the returns to VRT were negative (NRD < C).

Because the purchase of VRT applicators requires a large investment, most farmers hire VRT services from the farm supply sector (Snyder, 1996; Swinton and Ahmed, 1996). The methodology provided by English et al. (1998) could help farmers aspiring to custom hire VRT services discover whether the land mix on their fields could provide positive returns to VRT. The scope of their methodology, however, was restricted to the analysis of a field with only two land types. Farm fields, more often than not, are characterized by more than two land types. As such, the scope of the methodology in English et al. (1998) needs expanding. Farmers with more diverse field application based on the knowledge of two individual response functions, under variable rate application method. With Uniform Rate Technology (URT), optimization of N application was based on an average response function. The parameters of the average response function were weighted averages of the parameters of the two individual response functions, with proportions of the two land types in the field as weights. The Net Return Difference (NRD) that referred to the difference in optimum returns over variable costs between the two application methods was calculated for various proportions of the field in poor land. The authors located the minimum and maximum proportions of the field in poor land that bounded the proportions promising positive returns to VRT, i.e., the region where NRD was greater than the custom charges (C). The two limits of the region were referred to as *spatial break-even variability proportions*, since they enabled the farmer to just break even using the technology (NRD = C). When the proportion of the poor land on the field fall outside the range bounded by the two break-even variability proportions, the returns to VRT were negative (NRD < C).

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The objective of this study was to use the concepts in English et al. (1998) and develop a model to (i) ascertain spatial break-even variability proportions on fields with two or more land types, and (ii) identify the land mix that would maximize NRD. Impacts of changes in crop and input prices on spatial break-even variability and NRD maximizing proportions were also analyzed.

Methods

Suppose, in a particular location, lands suited to corn production can be classified into three groups: good land showing good yield response to applied nitrogen (N), medium land showing medium response, and poor land showing poor response to N. Suppose further that corn fields in the surrounding area can be characterized by any two or all three of these land types. The limitation to three land types is only a simplifying assumption. The methodology presented can be easily extended to fields with more than three land types with distinct yield response functions. This methodology is developed in the context of a corn field that has all the three land types, but fields involving only two land types are a subset of the three land-type case. Now, assume an A- acre field with A_g acres of good land, A_m acres of medium land and A_p acres of poor land. Assume further that the farmer is a profit maximizer with the following information on the three response functions.

$$Y_g = f_g(N_g) \qquad [1]$$

$$Y_m = f_m(N_m) \qquad [2]$$

and,

$$Y_p = f_p(N_p) \qquad [3]$$

Where Y_g, Y_m, and Y_p denote estimated corn yield (bu/acre) on the good, medium, and the poor land respectively; N_g, N_m, and N_p denote nitrogen applied (lb/acre) on good, medium, and poor land respectively. Under the variable rate application method, the profit maximizing farmer applies optimum N to each of the three land types based on the respective response functions (Equations 1-3). When following average rate application method, the farmer decides on the optimum amount of N application based on the average response function:

$$Y_a = f_a(N_a) \qquad [4]$$

Where Y_a denotes estimated average corn yield (bu/acre) for the field and N_a denotes the field average optimum nitrogen applied (lb/acre).

Variable Rate N Application

The profit maximizing farmer, when adopting VRT, applies N on each of the three land types planted to corn following the principle of economic optimality. Specifically, he/she uses knowledge of the yield response relationships (Equations 1-3) and applies N up to the point where marginal return equals marginal cost for the respective land types. Denoting corn and N prices as P_C and P_N, the respective optimality conditions for the good, medium and the poor lands can be expressed as:

$$f'_g = \frac{P_N}{P_C} \quad [5]$$

$$f'_m = \frac{P_N}{P_C} \quad [6]$$

$$f'_p = \frac{P_N}{P_C} \quad [7]$$

Expressions on the left hand side (LHS) of Equations 5, 6, and 7 are marginal physical productivities of N for the respective lands. When solved, these three Equations yield optimum N amounts, N_g^*, N_m^*, and N_p^*.

Optimum corn yields from the good, medium and the poor lands, denoted as Y_g^*, Y_m^*, and Y_p^*, can be estimated by substituting N_g^*, N_m^*, and N_p^* into Equations 1, 2, and 3 respectively. Optimum returns above N costs from the entire field, R^*_{VRA}, can then be estimated as:

$$R^*_{VRA} = A_g \times (P_C \times Y_g^* - P_N \times N_g^*) + A_m \times (P_C \times Y_m^* - P_N \times N_m^*) + A_p \times (P_C \times Y_p^* - P_N \times N_p^*) \quad [8]$$

Uniform Rate N Application

The optimum amount of N, when the farmer chooses to follow the average rate application method, is given by the following optimality condition based on Equation 4:

$$f'_a = \frac{P_N}{P_C} \quad [9]$$

Solving Equation 9 provides optimum average rate N application for the entire field, N_a^* and substituting N_a^* into Equation 4 provides optimum average corn yield from the field, Y_a^*. Optimum returns above N costs from the entire field under the uniform rate application method, R^*_{URA}, can then be estimated as:

$$R^*_{URA} = A \times (P_C \times Y_a^* - P_N \times N_a^*) \qquad [10]$$

Spatial Break-Even Variability and NRD Maximizing Variability

Net return difference (NRD) function

Given the yield response functions for the three land types (Equations 1-3), the magnitude of the difference between R^*_{VRA} and R^*_{URA} is determined by the proportion of each land type and corn and N prices (P_C and P_N). Referring to the difference (R^*_{VRA} - R^*_{URA}) as the Net Return Difference (NRD) following English et al. (1998) and denoting the proportions of good, medium and poor lands as Pr^g, Pr^m, and Pr^p respectively, the following functional relationship can be estimated.

$$NRD = f(Pr^g, Pr^p, P_C, P_N) \qquad [11]$$

Recall that the field is said to have spatial break-even variability, when the land proportions on the field ensure NRD = C. As such, determining break-even variability proportions requires resolving the optimality conditions till the equality between NRD and C is eventually reached. This process needs to be repeated each time P_C, P_N or C changes. The estimated NRD function (Equation 11), however, makes the estimation of break-even variability proportions much easier as illustrated later. Further, Equation 11 can be used with calculus to locate the land proportions that promise maximum NRD.

In Equation 11, the proportions of only two land types appear as the determinants of NRD. Since $Pr^g + Pr^m + Pr^p = 1$, specification of the proportions for two lands is sufficient.

Hypothesizing a functional form for Equation 11 involves certain considerations. Assuming that only good and poor lands could occupy the fields, NRD is zero when the field is all good land ($Pr^g = 1$ and $Pr^p = 0$) or all poor land ($Pr^p = 1$ and $Pr^g = 0$). When Pr^g decreases a little from 1 (or Pr^p increases above zero) and both land types occupy the field, optimization of input use with VRT becomes more accurate than with URT; as a result, NRD becomes positive. The NRD can be expected to increase as Pr^g continues to fall, but only over a certain range. When Pr^g decreases beyond certain value, NRD is expected to take a declining trend since the latter has to eventually reduce to zero with the field becoming devoid of good land ($Pr^g = 0$ and $Pr^p = 1$). This pattern of variation in NRD, however, is possible only if the optimum input application under VRT and URT is different. If the optimum input quantity is the same under both technologies, NRD just equals zero irrespective of the land mix. Suppose both good and poor lands are characterized by the linear-plus-plateau yield response functions with the same critical input application levels. Given that the price ratio is smaller than the linear coefficients of the two response functions, both land types receive the same non-zero input amount under VRT and URT.

The above explanation implies that NRD is in general quadratic in both Pr^g and Pr^p. Further, since we are considering here a field consisting of all the three land types, specification of certain value for Pr^g does not automatically determine the value of Pr^p;

it depends upon the value of Pr^m. In other words, Pr^p could assume several possible values such that $Pr^g + Pr^m + Pr^p = 1$ when Pr^g is given. Therefore, a change in NRD due to a small change in Pr^g can be expected to depend upon the magnitude of Pr^p and vice versa.

Given the land proportions, the magnitudes of P_C and P_N influence the magnitude of NRD through their influence on optimum returns above N cost under both application methods. Therefore, the effect on NRD of a given change in Pr^g or Pr^p is conditioned by the price variables. Also, the economic outcome under a given set of prices depends on the land mix in the field. The same prices could result in different NRD when the field is mostly good land compared to when the field is mostly medium or poor land. For this reason, the effect on NRD of a change in P_C or P_N could be expected to depend on Pr^g and Pr^p.

Considering possible interactions among Pr^g, Pr^p, P_C and P_N, Equation 11 can be expressed as:

$$\begin{aligned}\mathrm{NRD} = {} & \alpha_0 + \alpha_1 \times Pr^g + \alpha_2 \times Pr^g \times Pr^g + \alpha_3 \times Pr^p + \alpha_4 \times Pr^p \times Pr^p + \alpha_5 \times Pr^g \times Pr^p + \\ & \alpha_6 \times P_C + \alpha_7 \times P_N + \alpha_8 \times P_C \times P_N + \alpha_9 \times Pr^g \times P_N + \alpha_{10} \times Pr^g \times P_C + \\ & \alpha_{11} \times Pr^p \times P_N + \alpha_{12} \times Pr^p \times P_C + \alpha_{13} \times Pr^g \times P_N \times P_C + \alpha_{14} \times Pr^p \times P_N \times P_C + \\ & \alpha_{15} \times Pr^g \times Pr^p \times P_N + \alpha_{16} \times Pr^g \times Pr^p \times P_C + \alpha_{17} \times Pr^g \times Pr^p \times P_N \times P_C + e \qquad [12]\end{aligned}$$

Where NRD, Pr^g, Pr^p, P_C, and P_N are as explained earlier; e is a random error term; and $\alpha_0, \alpha_1 \ldots \alpha_{17}$ are parameters to be estimated by regression (SAS Institute, 1985).

Inclusion of the interaction terms $Pr^g \times Pr^p$, $P_C \times P_N$, $Pr^g \times P_N$, $Pr^g \times P_C$, $Pr^p \times P_N$, $Pr^p \times P_C$, $Pr^g \times P_N \times P_C$, $Pr^p \times P_N \times P_C$, $Pr^g \times Pr^p \times P_N$, $Pr^g \times Pr^p \times P_C$, and $Pr^g \times Pr^p \times P_N \times P_C$ in the model is based on the premise that the effect of any of the four variables, Pr^g, Pr^p, P_N, and P_C, on NRD depends on the values taken by these variables individually and in relation to others. Consider for example, the impact of a change in Pr^g on NRD. Differentiating Equation 12 with respect to Pr^g, gives $\alpha_1 + 2 \times \alpha_2 \times Pr^g + \alpha_5 \times Pr^p + \alpha_9 \times P_N + \alpha_{10} \times P_C + \alpha_{13} \times P_N \times P_C + \alpha_{15} \times Pr^p \times P_N + \alpha_{16} \times Pr^p \times P_C + \alpha_{17} \times Pr^p \times P_N \times P_C$. This expression shows that the effect of a change in Pr^g on NRD depends both on the individual magnitudes and the joint magnitudes (as reflected by the cross product terms) of these variables.

Spatial break-even variability proportions

English et al. (1998) defined spatial break-even variability proportions for a field with two land types as the minimum and the maximum proportions of the land types that allow the farmer to at least cover the additional cost of VRT (C). At these two extremes, the farmer just breaks even using VRT. Between these two land proportions, the farmer is better off using VRT and worse off otherwise. In contrast, the field under consideration includes three land types that could give several combinations of land proportions that enable the farmer to break even. Therefore, in the present context, spatial break-even variability proportions are the minimum and the maximum proportions of two land types, given the proportion of the third land type, so the farmer can at least cover the additional cost of VRT.

Denote the estimate of NRD (estimate of Equation 12) as $\widehat{NRD}$ and the estimate of α_i in Equation 12 as $\hat{\alpha}_i$. Given C, P_C, P_N, and either Pr^g or Pr^p, $\widehat{NRD}$ can be used to find spatial break-even variability proportions. Substituting the specific levels of P_C, P_N, and Pr^g, denoted as $\overline{P}_C$, $\overline{P}_N$ and $\overline{Pr}^g$, into $\widehat{NRD}$ and setting the resulting estimate equal to the specific level of C, denoted as $\overline{C}$, gives the following equation:

$$\overline{C} = \widehat{NRD} = (\hat{\alpha}_0 + \hat{\alpha}_1 \times \overline{Pr}^g + \hat{\alpha}_2 \times \overline{Pr}^g \times \overline{Pr}^g + \hat{\alpha}_6 \times \overline{P}_C + \hat{\alpha}_7 \times \overline{P}_N + \hat{\alpha}_8 \times \overline{P}_C \times \overline{P}_N + \hat{\alpha}_9 \times \overline{Pr}^g \times \overline{P}_N + \hat{\alpha}_{10} \times \overline{Pr}^g \times \overline{P}_C + \hat{\alpha}_{13} \times \overline{Pr}^g \times \overline{P}_N \times \overline{P}_C) + (\hat{\alpha}_3 + \hat{\alpha}_5 \times \overline{Pr}^g + \hat{\alpha}_{11} \times \overline{P}_N + \hat{\alpha}_{12} \times \overline{P}_C + \hat{\alpha}_{14} \times \overline{P}_C \times \overline{P}_N + \hat{\alpha}_{15} \times \overline{Pr}^g \times \overline{P}_N + \hat{\alpha}_{16} \times \overline{Pr}^g \times \overline{P}_C + \hat{\alpha}_{17} \times \overline{Pr}^g \times \overline{P}_N \times \overline{P}_C) \times Pr^p + \hat{\alpha}_4 \times Pr^p \times Pr^p \quad [13]$$

Since $\widehat{NRD}$ equals $\overline{C}$ at the spatial break-even variability proportions, solving Equation 13 provides those proportions. However, because $\widehat{NRD}$ in Equation 13 is obtained by regression, solutions may not exist (i.e., for $Pr^g = \overline{Pr}^g$, each possible value of Pr^p might imply NRD $\lesseqgtr$ C) or they might be infeasible (i.e., the solution might be such that $(\overline{Pr}^g + Pr^m + Pr^p) > 1$). The solutions for break-even variability proportions obtained in terms of Pr^p can be expressed in terms of Pr^m using the relationship $Pr^m = 1 - \overline{Pr}^g - Pr^p$.

Equation 13 can also be used to find solutions for break-even variability proportions of good land given $Pr^p = \overline{Pr}^p$. Further, break-even variability proportions, given $Pr^m = \overline{Pr}^m$, can be found after expressing $\widehat{NRD}$ in Equation 13 in terms of Pr^m and either Pr^g or Pr^p.

<u>NRD maximizing land proportions</u>

Given $\overline{Pr}^g$, the NRD maximizing Pr^p or Pr^m can be found from Equation 13, by taking the first derivative with respect to Pr^p, setting it equal to zero, and then solving the resulting equation for Pr^p or Pr^m. Given $\overline{Pr}^m$, finding the NRD maximizing proportions requires expressing $\widehat{NRD}$ in Equation 13 in terms of Pr^m and either Pr^g or Pr^p.

Spatial break-even variability proportions as well as NRD maximizing proportions for a field consisting of only two land types can be obtained using the methodological framework developed for a field with all the three land types. Say for example, a field consists only of medium and poor lands. For this situation, solving Equation 13 after setting $Pr^g = \overline{Pr}^g = 0$ provides solutions in terms of Pr^p. Solutions in terms of Pr^m can be obtained from $Pr^p + Pr^m = 1$.

Application to a Hypothetical Field

The methods developed in the previous sections were illustrated by applying them to four hypothetical corn fields of 100 acre each. One of the four fields consisted of all the three land types. The land types assumed to be present in the remaining fields were good and medium, medium and poor, and good and poor. Several studies on corn yield response to applied N have used quadratic yield response models (Cerrato and Blackmer, 1990; Lichtenberg et al., 1994). Accordingly, this study used the following hypothetical corn yield response functions for good, medium, and poor lands.

$$Y_g = 120 + 1.11 \times N_g - 0.0023 \times N_g \times N_g \quad [14]$$

$$Y_m = 100 + 1.05 \times N_m - 0.0026 \times N_m \times N_m \quad [15]$$

and,

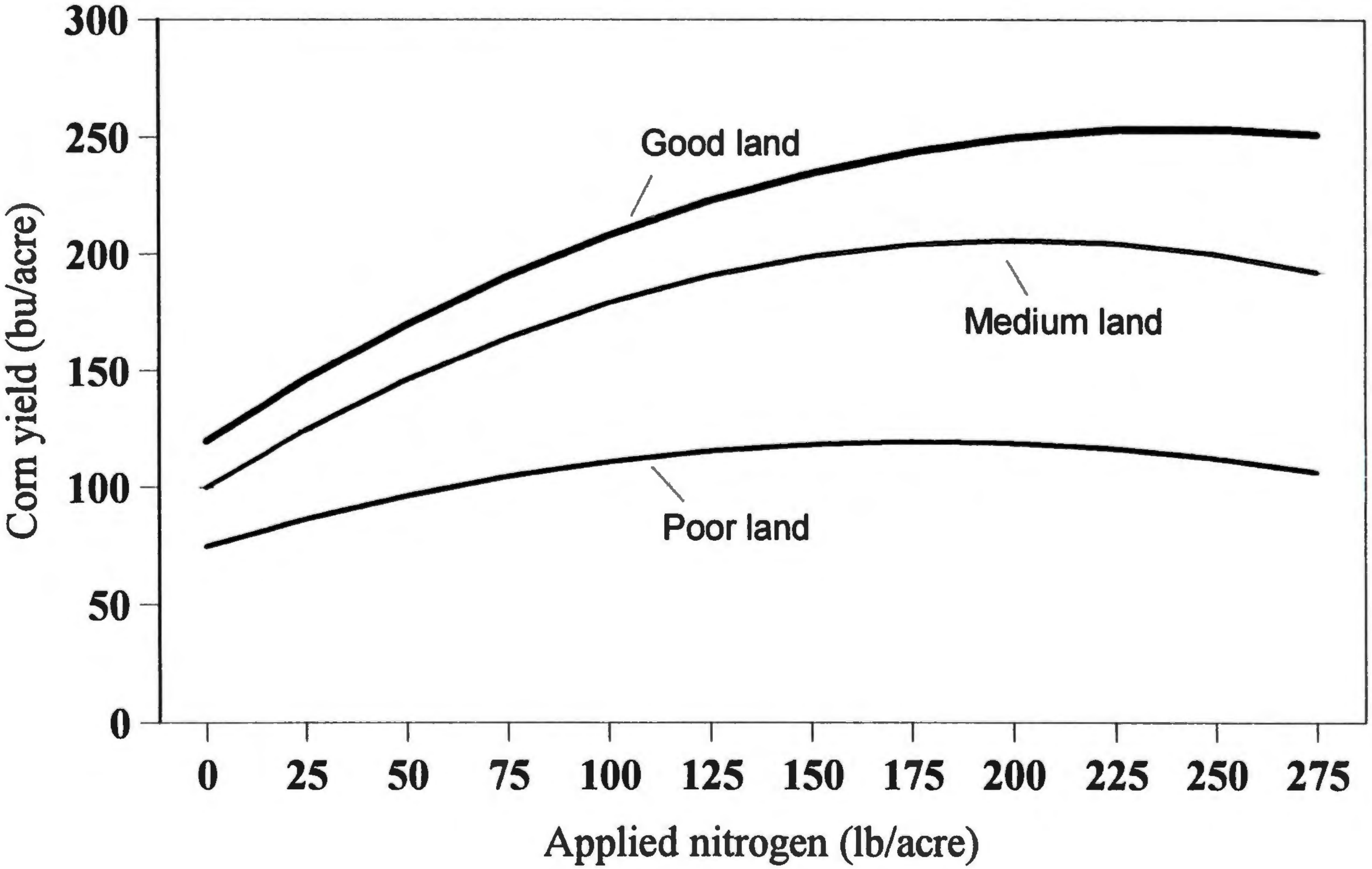
$$Y_p = 75 + 0.5 \times N_p - 0.0014 \times N_p \times N_p \quad [16]$$

According to the above functions, the marginal physical productivity of applied nitrogen was highest on good land, lowest on poor land, and in between on medium land. Figure 1 graphically depicts the hypothetical yield response functions for the three land types.

The parameters of the average response function (Equation 4) were weighted averages of the parameters of the individual response functions for the land types present on the field, with the proportions of the respective lands as the weights (English et al., 1998).

For estimating the NRD function (Equation 12) a series of NRD's were generated by varying (i) the proportion of each of the three land types in the 100-ac field from 0% to 100% in 10% increments (ii) P_C from \$2/bu to \$4/bu in \$0.50 increments, and (iii) P_N from \$0.20/lb to \$0.40/lb in \$0.05 increments (N source was urea). The ranges for P_C and P_N were decided looking at the prices reported in several issues of *Tennessee Agriculture* (Tennessee Department of Agriculture/Tennessee Agricultural Statistical Service).

Figure 1. Hypothetical Corn Yield Response Functions



Break-even analysis and maximum NRD analysis were first conducted for the 1993-1997 mean corn and nitrogen prices of $\overline{P}_C$ = \$2.79/bu and $\overline{P}_N$ = \$0.26/lb. Additional custom charges for variable rate application were assumed to be $\overline{C}$ = \$300 (@ \$3/ac) (R.K. Roberts, personal communication, November 1998). Later, the sensitivity of the results to the changes in P_C and P_N was examined.

Results

All estimated coefficients, except six, of NRD function were statistically significant (Table 1). The high R^2 value suggested that more than 98 percent of the variation in NRD was explained by the explanatory variables of the model. Further, F-value suggested the overall fit of the regression was highly significant. The variables Pr^g and Pr^p and their quadratic terms had expected signs.

Spatial Break-Even Variability and NRD Maximizing Variability

Field with three land types

Table 2 presents NRD maximizing variability proportions as well as spatial break-even variability proportions for a hypothetical field consisting of all the three land types, assuming $\overline{P}_C$ = \$2.79/bu, $\overline{P}_N$ = \$0.26/lb, and $\overline{C}$ = \$300. When calculating these proportions, one of the three land types in the field was assumed to be 20%, 40%, 60%, or 80% of the total field area. When the share of good or medium land was specified, both NRD maximizing land proportion and spatial break-even variability proportion were calculated in terms of poor land. When, on the other hand, the share of poor land in the field was specified, the proportions were calculated in terms of medium land.

Table 1. Estimated Net Return Difference (NRD) Function

Variable	Coefficient	T-statistic	Variable	Coefficient	T-statistic
Intercept	-255.514*	-7.005	$Pr^g \times P_C$	-13.354	-0.590
Pr^g	1142.826*	16.118	$Pr^p \times P_N$	375.192‡	1.657
$Pr^g \times Pr^g$	-1019.582*	-81.823	$Pr^p \times P_C$	-36.857	-1.628
Pr^p	821.029*	11.579	$Pr^g \times P_N \times P_C$	49.073	0.668
$Pr^p \times Pr^p$	-703.779*	-56.479	$Pr^p \times P_N \times P_C$	-26.363	-0.359
$Pr^g \times Pr^p$	-1617.693*	-6.984	$Pr^g \times Pr^p \times P_N$	3725.940*	4.970
P_C	62.990*	5.335	$Pr^g \times Pr^p \times P_C$	628.182*	8.380
P_N	314.049*	2.660	$Pr^g \times Pr^p \times P_N \times P_C$	-168.706	-0.694
$P_N \times P_C$	-40.743	-1.064	R^2	0.983	
$Pr^g \times P_N$	-500.264†	-2.210	F	5649.577	

* Significant at the $\alpha = 0.01$ level; † Significant at the $\alpha = 0.05$ level; ‡ Significant at the $\alpha = 0.10$ level.

Table 2. Net Return Difference (NRD) Maximizing Land proportions and Spatial Break-Even Variability Proportions in a Hypothetical 100-Acre Corn Field with Good, Medium, and Poor Lands

Assumed Value of Pr^g, Pr^m or Pr^{p*} on the Field	NRD Maximizing Proportion	Maximum Possible NRD	Spatial Break-Even Variability Proportion† Minimum Proportion	Maximum Proportion
................(percent)................		($)	............(percent)............	
<u>Assumed value of Pr^g</u>	<u>In terms of Pr^p</u>		<u>In terms of Pr^p</u>	
20.00	70.54	483.95	19.41	No limit
40.00	60.00	673.76	7.61	No limit
60.00	40.00	653.49	6.58	No limit
80.00	20.00	416.85	11.41	No limit
<u>Assumed value of Pr^m</u>	<u>In terms of Pr^p</u>		<u>In terms of Pr^p</u>	
20.00	40.71	576.82	8.71	72.70
40.00	29.54	447.91	6.15	52.92
60.00	18.37	304.91	14.11	22.63
80.00	7.20	147.79	No solution††	No solution
<u>Assumed value of Pr^p</u>	<u>In terms of Pr^m</u>		<u>In terms of Pr^m</u>	
20.00	20.79	460.93	No limit	60.52
40.00	00.00	653.49	No limit	50.71
60.00	00.00	673.76	No limit	33.27
80.00	00.00	477.65	No limit	11.78

* Pr^g, Pr^m, and Pr^p refer to the proportions of good, medium, and poor lands in the field, respectively.

† When Pr^g or Pr^m are assumed, both NRD maximizing proportion and spatial break-even variability proportion are calculated in terms of Pr^p; when Pr^p values are assumed, they are calculated in terms of Pr^m.

†† When Pr^m = 80, the maximum NRD ($147.79) itself is less than the VRT custom charges ($300); therefore, no proportion of poor land enables the farmer to at least break even using the technology.

As Table 2 reveals, given 20% good land on the field, 70.54% poor land (alternatively, (100 - 20 - 70.54)% or 9.46% medium land) would yield a maximum NRD of around \$485. Similarly, given 20% medium land, 40.71% poor land would yield a maximum NRD of around \$575; and, given 20% poor land, 20.79% medium land would assure a maximum NRD of \$460. The table also shows that when 40%, 60% or 80% of the field area was under good land, maximum NRD could be achieved only when poor land entirely occupied the remaining field area. For example, given 40% good land, a maximum NRD of \$673.76 could be generated when poor land occupied the remaining 60% field area. Similarly, given 40%, 60% or 80% of the field under poor land, NRD kept rising as the share of medium land decreased; maximum NRD could be generated when the field was completely devoid of medium land. For example, when poor land was 40% of the field, NRD could reach a maximum of \$653.49 with no medium land or, alternatively, 60% good land on the field.

Table 2 also presents spatial break-even variability proportions. When good land was assumed to occupy 20%, 40%, 60% or 80% of the field, spatial break-even variability analysis prescribed only the minimum share of poor land for VRT implementation. The results did not suggest any upper limits on the share of poor land so the farmer would incur no losses by implementing VRT. For example, when good land occupied 40% of the field, a minimum of 7.61% poor land was required so the farmer could at least break-even custom hiring VRT services. With less than 7.61% poor land, the farmer would incur economic losses from VRT adoption. The results, however, did not suggest any upper limit on the proportion of this land. This implied that NRD equaled \$300 with 7.61% poor land and, thereafter, kept increasing without any declining trend as more and more of the field was occupied by poor land. Therefore, given 40% good land, the farmer would be economically safe with VRT if he/she just ensured that the field had the minimum suggested poor land. Notice how the minimum requirements of poor land varied depending upon the proportion of good land in the field.

Given 20%, 40%, 60% or 80% of the field under poor land, the results indicated only the upper limits on the share of medium land so the adoption of VRT would be economically feasible. As an example, when 40% of the field was poor land, the farmer could afford to have a maximum of 50.71% medium land for economically safe VRT adoption. With that much of medium land, the farmer could just break even using custom hired VRT services and beyond that limit, he/she would only suffer negative returns to VRT. The results indicated no minimum requirement of medium land, which implied that given 40% poor land, smaller the share of medium land, better it was economically for the farmer. Notice again that the limits on the maximum share of medium land for VRT adoption varied depending upon the extent of poor land.

Notice one particular circumstance under which solutions for spatial break-even variability proportions did not exist. When the share of medium land on the field was 80%, the maximum possible NRD (\$147.79) itself was much less than \$300, the amount of custom charge; no land mix could enable the farmer to offset custom charges. Therefore, this particular case suggested that given 80% medium land, P_C = \$2.79/bu, P_N = \$0.26/lb and C = \$300, the farmer should not try to implement VRT since by doing so he/she would just incur losses.

Field with only two land types

The NRD maximizing proportions and spatial break-even variability proportions for the fields with only two land types are presented in Table 3. As the table reveals, VRT adoption on the fields consisting of good and medium lands or medium and poor lands was not economically feasible. In these two cases, the maximum NRD that could be generated ($223.00 and $197.76 respectively) was much less than $300, the charges for custom services. As such, the solutions for spatial break-even variability proportions did not exist in these two cases. In other words, no mix of good and medium lands or medium and poor lands could enable the farmer to obtain enough NRD to offset custom charges. Therefore, given the assumed prices, custom charges, and yield response relationships, the farmers cultivating these two types of field would do better without VRT from the economic view point.

Adoption of VRT on the field that had good and poor lands, however, was found to have economic potential. As Table 3 shows, 51.87% poor land on this kind of field could fully exploit the economic potential of VRT by generating a maximum NRD of $690. The results also indicated that the farmer seeking to adopt VRT on this kind of field had to make sure that the share of poor land on the field ranged between 13.82% and 89.93%. At these two extremes, the farmer could just break even. When the proportion of poor land fell between these extremes, the farmer could enjoy positive returns to VRT and when it was less than 13.82% or more than 89.93%, the farmer suffered negative returns.

Table 3. Net Return Difference (NRD) Maximizing Land Proportions and Spatial Break-Even Variability Proportions in a Hypothetical100-Acre Corn Field Consisting of Two Land Types

Land Types Present in the Field	NRD Maximizing Proportion[†]	Maximum Possible NRD	Spatial Break-Even Variability Proportion[†]	
			Minimum Proportion	Maximum Proportion
	(percent)	($)	.............(percent).............	
	In terms of Pr^m[‡]		In terms of Pr^m	
Good and medium	50.42	223.00	No solution[¶]	No solution
	In terms of Pr^p		In terms of Pr^p	
Good and poor	51.87	691.62	13.82	89.93
	In terms of Pr^p		In terms of Pr^p	
Medium and poor	56.60	197.76	No solution[¶]	No solution

[†] When the field consists of good and medium lands, both NRD maximizing proportion and spatial break-even variability proportion are calculated in terms of Pr^m; when the field consists of good and poor lands or medium and poor lands, they are calculated in terms of Pr^p.

[‡] Pr^m and Pr^p refer to the proportions of medium and poor lands in the field, respectively.

[¶] Maximum NRD itself is less than the VRT custom charges of $300; therefore, no land proportions on the field enable the farmer to at least break even using the technology.

Sensitivity Analysis

As seen above, the NRD function and custom charges were the determinants of spatial break-even variability proportions. However, it may be noted that given yield response relationships for different land types on the field, nitrogen and corn prices, P_N and P_C, determine NRD function. A sensitivity analysis, therefore, was conducted to examine how the changes in P_N and P_C could influence spatial break-even variability proportions and NRD maximizing proportions through their impact on NRD. To keep the analysis short, a field with all the three land types was considered assuming that it was either 20% or 40% medium land. Table 4 presents the results. For purposes of better comparison, corresponding results from Table 2, which were obtained with base

Table 4. Impact of Changes in Nitrogen and Corn Prices (P_N and P_C) on Net Return Difference (NRD) Maximizing Land Proportions and Spatial Break-Even Variability Proportions in a Corn Field with All Three Land Types

Assumed Value of Pr^m* on the Field	Changes in P_N and P_C Examined	NRD Maximizing Proportion†	Maximum Possible NRD	Spatial Break-Even Variability Proportion†	
				Minimum Proportion	Maximum Proportion
(Percent)		(Percent)	($)	......(Percent)......	
20	**Base prices**	**40.71**	**576.82**	**8.71**	**72.70**
	Rise in P_N by 5%	40.85	585.94	8.59	73.12
	Rise in P_C by 5 %	40.58	594.66	8.06	73.10
	Fall in P_N by 5%	40.55	567.71	8.84	72.26
	Fall in P_C by 5%	40.84	558.99	9.42	72.26
40	**Base prices**	**29.54**	**447.91**	**6.15**	**52.92**
	Rise in P_N by 5%	29.70	454.05	6.02	53.38
	Rise in P_C by 5%	29.44	460.73	5.42	53.46
	Fall in P_N by 5%	29.37	441.79	6.29	52.45
	Fall in P_C by 5%	29.64	435.10	6.94	52.33

* Pr^m refers to the proportion of medium land.

† NRD maximizing proportion and spatial break even variability proportion are both expressed in terms of Pr^p, the proportion of poor land.

prices, are reproduced in Table 4.

As the table shows, given 20% or 40% medium land, NRD maximizing proportion of poor land varied directly with P_N and inversely with P_C. In other words, the proportion increased as a result of a rise in P_N or a fall in P_C and decreased as a result of a fall in P_N or rise in P_C. However, the maximum NRD that could be obtained increased with an increase in both price variables and vice versa. Notice that irrespective of whether the field was 20% or 40% medium land, a 5% change in P_C had a larger impact on the amount of maximum NRD compared to 5% change in P_N. The sensitivity analysis also revealed that increase in P_N as well as P_C expanded the range of variability of poor land over which positive returns to VRT were possible. In other words, the minimum requirement of poor land for VRT adoption decreased and the maximum proportion beyond which VRT led to losses increased. With a fall in P_N or P_C, the economically viable range of variability decreased. In other words, the minimum requirement of poor land increased and the upper limit on the proportion of this land decreased.

Conclusions

This study argues that the choice between variable rate and uniform rate application of inputs on a farm field depends to a large extent on the expected economic benefits from the new technology. Since economic benefits from VRT are in fact returns to treating within-field variability, a careful examination of the magnitude and nature of the variability is important in decisions regarding VRT adoption. All fields in general reveal variability; however, not all fields warrant VRT from a purely economic standpoint. In other words, it is possible that a field might exhibit variability which, when treated differentially, only adds to costs putting the farmers in a financial distress. In this context, the concept of spatial break-even variability (English et al., 1998) assumes significance since it explains what kind of within-field variability can enable the farmers to, at least, offset the costs of implementing VRT.

English et al. (1998) developed the concept of spatial break-even variability in the context of a farm field that included only two land types. This simulation study developed an analytical framework that could help identify spatial break-even variability in the fields having two or more land types. Further, the methods developed could help find the variability that would result in maximum additional returns with variable rate application of inputs.

For the sake of simplicity, the study considered only three land types showing varying corn yield responses to applied N. Either all the three or any two of these land types occupied hypothetical 100-acre corn fields in the analysis. Spatial break-even variability analysis requires, in addition to the knowledge of yield response relationships, the information on input and product prices and the cost of technology. The present study considered five-year average (1993-1997) prices of N and corn ($0.26/lb and $2.79/bu) and VRT custom charges of $300 (@3/ac). Urea fertilizer was assumed to be the source of N. When analyzing the field with all the three land types, the share of one of the lands was specified at certain level.

The results indicated that spatial break-even variability proportions varied depending upon the proportion specified of one of the three land types. When good land was 20%, 40%, 60% or 80% of the field, the farmer was only required to make sure that the field had certain minimum proportion of poor land, before choosing to adopt VRT. He/she did not have to worry about the maximum proportion of poor land on the field. When, instead, the proportion of poor land was specified, the farmer had to only make sure that medium land did not exceed certain limit. There was no minimum requirement of medium land. When the share of medium land on the field was specified to be 20%, 40% or 60%, both minimum and maximum break-even variability proportions were clearly specified in terms of poor land.

With respect to the fields that had only two land types, the results suggested that no land mix could justify VRT adoption when the field consisted of good and medium lands or medium and poor lands. The study also analyzed the land mix that could maximize NRD on each of these fields. Finally, the impacts of changes in nitrogen and corn prices on NRD maximizing proportions and break-even variability proportions were investigated. An increase in corn and nitrogen prices could increase NRD and hence, expand the range of variability that promised positive returns to VRT. A fall in prices had opposite effects.

Given the information on yield response functions characterizing the field, the crop and input prices and custom charges, the methodology developed in this study could be used to estimate (i) differential returns that could be realized with VRT (ii) spatial break-even variability proportions, and (iii) NRD maximizing proportions. The framework developed here can easily incorporate changes in input and product prices and custom charges.

Finally, it needs to be mentioned that the land classification in the study as good, medium and poor one is crop specific. The classification on the same field could be different, when different crops with different responses to applied N are considered. As such, spatial break-even variability proportions for VRT adoption are crop specific too. Further, a better classification of land for a given crop could be possible when precision farming technology is used to identify the factors that limit yield response to applied inputs across the field and to correct the existing limitations.

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Part 4: Economic and Environmental Benefits of Precision Farming: Role of Variability, Weather and Public Policy

Introduction

The concept of precision farming or site-specific farming is gaining popularity in recent years. The growing interest in the concept is driven by both economic and environmental considerations.

Farmers have traditionally been treating farm fields as homogeneous units and applying inputs at uniform rates. Such practice does not match input application to plant and soil needs and hence results in under- and over-applications across the field (Carr et al., 1991; Hannah et al., 1982; Karlen et al., 1990; Malzer et al., 1996).

Precision farming addresses site-specific crop needs. Its component technologies help farmers understand changing plant growth environment across the field, estimate nutrient requirements, and apply inputs on a site-specific basis. It is claimed that precision farming, by placing right quantities of inputs in right places, helps farmers enjoy greater economic benefits, while reducing environmental harms associated with excessive use of agricultural inputs (Kitchen et al., 1996; Koo and Williams, 1996; National Research Council, 1997; Sawyer, 1994; Watkins et al., 1998).

Several studies have assessed the economic potential of Variable Rate Technology (VRT) (Carr et al., 1991; English et al., 1998; Fiez et al., 1994; Forcella, 1993; Hayes et al., 1994; Hibbard et al., 1993; Snyder, 1996; Wibawa et al., 1993). However, most earlier studies ignored the effects of variable rate input application on environment (Watkins et al., 1998; Lowenberg-DeBoer, 1996; Swinton and Ahmed, 1996). Losses of agricultural chemicals, especially Nitrate Nitrogen (NO_3-N), into ground water have been a continuing concern for society. If Site-Specific Management

(SSM) practices are deemed beneficial for water quality, a public policy could evolve to reduce the cost of technology and encourage its adoption (Swinton and Ahmed, 1996). Therefore, more economic research needs to be conducted to test the hypothesis of environmental benefits associated with the new technology (Lowenberg-DeBoer and Swinton, 1995).

The literature on precision farming has also largely ignored one of the important sources of risk for VRT – temporal yield variability (Lowenberg-DeBoer and Swinton, 1995). Weather constitutes an important source of uncertainty in agriculture. Fluctuating weather patterns could cause large variations in crop yields and farm profits. If the crop management decisions do not fit the imminent weather conditions, farm operators could either incur losses or miss the higher economic gains. As such, farmers try to develop an expectation regarding the uncertain crop growing conditions and perform the field operations accordingly. While farmers benefit from correct weather expectations, they could suffer economic losses when the expectations go wrong. Given that the expectations regarding uncertain weather are likely to go wrong, it would be interesting to analyze and compare their economic consequences for precision farming and uniform rate application method. Such an analysis would indicate whether the economic potential of the new technology is more or less sensitive to weather conditions compared to the traditional method.

The present study addresses the above issues assuming that the farmers practice precision farming with VRT services custom hired from the farm supply sector if the expected additional returns from the technology adoption at least equal the custom charges. The study seeks to address these issues in the context of varying degrees of spatial variability (distribution in the field of lands with different production capabilities).

The specific objectives of the study were (i) to examine the economic feasibility of variable rate N application on the corn fields exhibiting different patterns of spatial variability, (ii) to illustrate the role of weather expectations in precision farming, (iii) to test the hypothesis that precision farming holds the promise of environmental benefits, and (iv) to examine policy options to motivate farmers to adopt precision farming if the new technology is found to reduce environmental degradation.

Methods

Data

Corn yield and N loss

The Environmental Policy Integrated Climate (EPIC) crop growth model was used to generate necessary data on corn yield and N loss in leaching, surface runoff and sub surface flow. EPIC was developed to estimate erosion and productivity relationships. However, the simulation model has much greater potential and can be used to examine water quality impacts as well as productivity impacts of alternative farming systems (Benson, 1989).

The input data set for EPIC included three important soil series of West Tennessee suited to growing corn. The soils were deep Collins (0% slope with no fragipan), Loring (3% slope with 30" depth to fragipan) and deep Memphis (1% slope with no fragipan) (D.D. Tyler, personal communication, June 1998). According to EPIC data files, the depth from surface to the bottom of soil layer in respect of Collins and

Memphis series was more than 70 inches. The management operations inputted into EPIC included plowing with chisel plow and single disking and thus represented a reduced tillage. Based on Epic data files, residue cover was greater than 30% after planting. This qualifies as a reduced tillage practice as defined by the National Resource Conservation Service (B.C. English, Personal Communication, November 1998).

Monthly rainfall data recorded by Covington weather station in West Tennessee were taken from several issues of *Climatological data, Tennessee* (US Department of Commerce/National Oceanic and Atmospheric Administration (NOAA)) and five rainfall scenarios were created and inputted into EPIC input data set. Specifically, scenario-I was constituted with average rainfall amounts for each of the twelve months over the period 1988-1997; scenario-II and scenario-III were created by decreasing the monthly averages in scenario-I by 0.5 standard deviation and 1 standard deviation, respectively; and, scenario-IV and scenario-V were created by increasing the monthly average values by these magnitudes. EPIC was forced to generate adjusted weather so the mean monthly minimum and maximum temperatures and the mean monthly precipitation for each year of simulation would be the same as the mean monthly values in the input data set.

Yield and N loss data were generated through EPIC simulations for twenty-five years for eight N application levels ranging from 0 to 280 lb/acre in 40-lb increments.

Corn and N prices and VRT custom charges

The present analysis was conducted with corn price (P_C) = \$2.79/bu, a five-year average over 1993-1997 and N price (P_N) = \$0.26/lb, a five-year average over the same period assuming that the source of N was urea fertilizer (Tennessee Department of

Agriculture/Tennessee Agricultural Statistical Service). The additional custom charge the farmer has to bear when he/she chooses variable rate application of N instead of uniform rate application was assumed to be \$3/acre (R.K. Roberts, personal communication, November 1998).

Corn Yield Response Functions for Applied N

Economic analysis of crop production regardless of the technology used requires determining the responsiveness of crop yields to inputs (Snyder, 1996). For this study, the yield response functions were obtained by estimating metamodels – the sub models of EPIC simulation model. A metamodel estimates or approximates the response surface of a simulation model. As such, it can be used to study how the response would change if certain input factors were changed slightly and to find approximately optimal settings of the input factors (Law and Kelton, 1991).

Preliminary analysis of the data generated with EPIC suggested that yields increased at a decreasing rate up to certain level of N application and thereafter, a plateau was formed. Therefore, the following quadratic-plus-plateau yield response model was specified for each soil under each rainfall scenario:

$$Y = \alpha + \beta \times N + \gamma \times N \times N \text{ if } N < N^c \quad [1]$$

$$Y = Y^p \qquad \text{if } N \geqslant N^c \quad [2]$$

Where Y = corn yield (bu/acre); N = N application rate (lb/acre); α, β and γ are intercept, linear coefficient and quadratic coefficient respectively, obtained by fitting the model to the data; and, N^c and Y^p are critical N rate and plateau yield, also obtained by fitting the model.

Literature on corn yield response to applied N provides the cases in which quadratic-plus-plateau model better explained yield responses compared to the other models considered (Bullock and Bullock, 1994; Cerrato and Blackmer, 1990; Decker et al., 1994). NLIN procedure (SAS Institute, 1985) was used to estimate the model.

While the farmer uses his/her knowledge of response functions for individual soil types in the field when following variable rate N application, he/she relies on the knowledge of field average response function when following uniform rate application method. Therefore, the field average quadratic-plus-plateau models were also estimated for each of the hypothetical study field described in the next section.

Hypothetical Study Fields

In order to illustrate the influence of spatial variability on economic and environmental impacts of precision farming, a total of thirty-six hypothetical fields were created by varying the proportions of each of the three soil types from 10% to 80% in 10% increments. Table 1 presents these study fields.

Economic Analysis of Precision Farming

This study assumes that the farmer is a profit maximizer. The study also assumes that the farmer possesses the knowledge of the response functions for the three individual soil types in the field as well as the field average response function under all the three rainfall scenarios. With these assumptions, the economic analysis was first conducted to examine how many of the thirty-six corn growers would benefit from variable rate N application, given that their weather predictions go right. Later, the economic consequences of going for VRT were analyzed, assuming that the farmers' weather

Table 1. Proportions of Collins, Memphis and Loring Soils on Thirty-six Hypothetical Corn Fields

Field No.	Land Proportions in the Field			Field No.	Land Proportions in the Field		
	Collins	Memphis	Loring		Collins	Memphis	Loring
1	10	10	80	19	30	40	30
2	10	20	70	20	30	50	20
3	10	30	60	21	30	60	10
4	10	40	50	22	40	10	50
5	10	50	40	23	40	20	40
6	10	60	30	24	40	30	30
7	10	70	20	25	40	40	20
8	10	80	10	26	40	50	10
9	20	10	70	27	50	10	40
10	20	20	60	28	50	20	30
11	20	30	50	29	50	30	20
12	20	40	40	30	50	40	10
13	20	50	30	31	60	10	30
14	20	60	20	32	60	20	20
15	20	70	10	33	60	30	10
16	30	10	60	34	70	10	20
17	30	20	50	35	70	20	10
18	30	30	40	36	80	10	10

expectations were wrong.

Accurate weather expectations and economic gains from VRT

To fix the ideas, let us consider any one of the study fields and assume that the farmer expects rainfall scenario-I to occur. Let us now proceed to find the economic viability of VRT adoption on this field assuming the expected rainfall scenario occurs. As per the assumption of the study, the soil-specific response functions along with the field average response function for rainfall scenario-I are known. The response function, for example, for Loring soil can be written as:

$$Y_{Lr} = \alpha_{Lr} + \beta_{Lr} \times N + \gamma_{Lr} \times N \times N, \text{ if } N < N^{c}_{Lr} \quad [3]$$

$$Y_{Lr} = Y^{P}_{Lr}, \text{ if } N \geqslant N^{c}_{Lr} \quad [4]$$

Where Y_{Lr} = corn yield on Loring soil (bu/acre); N = N application rate (lb/ac); α_{Lr}, β_{Lr} and γ_{Lr} are the coefficients specific to Loring soil under rainfall scenario-I, obtained by fitting the model to the data; $N^c{}_{Lr}$ is the critical N rate for Loring under rainfall scenario-I; and, $Y^P{}_{Lr}$ is the plateau yield.

Similarly, the response functions for Collins and Memphis soils can be written as:

$$Y_{Cl} = \alpha_{Cl} + \beta_{Cl} \times N + \gamma_{Cl} \times N \times N, \text{ if } N < N^c{}_{Cl} \quad [5]$$

$$Y_{Cl} = Y^P{}_{Cl}, \text{ if } N \geqslant N^c{}_{Cl} \quad [6]$$

and,

$$Y_{Mp} = \alpha_{Mp} + \beta_{Mp} \times N + \gamma_{Mp} \times N \times N, \text{ if } N < N^c{}_{Mp} \quad [7]$$

$$Y_{Mp} = Y^P{}_{Mp}, \text{ if } N \geqslant N^c{}_{Mp} \quad [8]$$

The field average response function can be written as:

$$Y_{Fld} = \alpha_{Fld} + \beta_{Fld} \times N + \gamma_{Fld} \times N \times N, \text{ if } N < N^c{}_{Fld} \quad [9]$$

$$Y_{Fld} = Y^P{}_{Fld} \text{ if } N \geqslant N^c{}_{Fld} \quad [10]$$

Given corn and N prices (P_C and P_N), the economic optimum N rate can be determined from the quadratic phase of the model by taking the first derivative with respect to N, setting it equal to the ratio of P_N to P_C, and then solving the resulting equation. For example, the optimum N rate for Loring soil, denoted as $N^*{}_{Lr}$ is calculated as:

$N^*{}_{Lr} = \dfrac{(P_N \div P_C) - \beta_{Lr}}{2 \times \gamma_{Lr}}$, if $\dfrac{(P_N \div P_C) - \beta_{Lr}}{2 \times \gamma_{Lr}} \leqslant N^c{}_{Lr}$ (the critical N rate) and

$N^*{}_{Lr} = N^c{}_{Lr}$, if $\dfrac{(P_N \div P_C) - \beta_{Lr}}{2 \times \gamma_{Lr}} > N^c{}_{Lr}$. Assume for this illustration that the optimum N application rates, $N^*{}_{Lr}$ (for Loring), $N^*{}_{Cl}$ (for Collins), $N^*{}_{Mp}$ (for Memphis), and $N^*{}_{Fld}$

(the field average application rate) are all less than the respective critical N values so the quadratic phases of the respective response functions explain the yield responses.

Denote the optimum yields (bu/acre) under rainfall scenario-I as Y^{*}_{Lr} for Loring, Y^{*}_{Cl} for Collins, Y^{*}_{Mp} for Memphis, and Y^{*}_{Fld} for the field as a whole. These optimum yields can be obtained by plugging the optimum N rates into the equations for the quadratic phases of respective yield response models. For example, Y^{*}_{Lr} can be obtained by plugging N^{*}_{Lr} in to Equation 3. Now, we can express the total optimum returns above N costs from the field under rainfall scenario-I with VRT as:

$$R^{*}_{VRT} = A_{Lr} \times (P_C \times Y^{*}_{Lr} - P_N \times N^{*}_{Lr}) + A_{Cl} \times (P_C \times Y^{*}_{Cl} - P_N \times N^{*}_{Cl}) +$$

$$A_{Mp} \times (P_C \times Y^{*}_{Mp} - P_N \times N^{*}_{Mp})$$

Where A_{Lr} = total area under Loring series in the field; A_{Cl} = area under Collins, and A_{Mp} = total area under Memphis series. Similarly, the optimum returns above N costs from the field under Uniform Rate Technology (URT) can be found as:

$$R^{*}_{URT} = (A_{Lr} + A_{Cl} + A_{Mp}) \times (P_C \times Y^{*}_{Fld} - P_N \times N^{*}_{Fld}).$$

Refer to the difference $R^{*}_{VRT} - R^{*}_{URT}$ as the Net Return Difference (NRD) following English et al (1998). With C as the additional custom charges the farmer has to pay for variable rate N application, the necessary condition for VRT adoption on this field is NRD $\geqslant$ C. Suppose that NRD is in fact greater than C. This means that the farmer operating this particular field can decide to go for VRT when he/she expects rainfall scenario-I and enjoy economic gains. Note an important thing in this context: the economic benefits from VRT for the farmer in this illustration is subject to the condition that rainfall scenario-I does occur as expected.

The above procedure was followed for each study field under each rainfall scenario to find how many corn growers would benefit economically with VRT, given that their rainfall expectations are right.

Inaccurate weather expectations and economic consequences for VRT

Suppose the operator of the field considered in the above illustration custom hires VRT services and applies optimum N amounts believing that rainfall scenario-I occurs, but actually, rainfall scenario-II occurs. Since the parameters of the response functions for rainfall scenario-II could be different from the ones for scenario-I, N applications on the individual soil types might not evoke the expected yield responses. As a result, the farmer might not generate enough additional returns to offset the custom charges; he might even generate negative additional returns with VRT. The consequence of switching to VRT from URT with a wrong prediction of weather, therefore, could be a financial loss to the farmer. The study examined the role of weather expectations in precision farming. This was accomplished by finding whether VRT would economically harm or still benefit the farmers who decide to go for it based on their weather expectations that eventually turn out to be wrong.

Environmental Analysis of Precision Farming

The study analyzed the environmental consequences of N application under both URT and VRT. Following Chowdhury and Lacewell (1996) and Wu et al. (1996), environmental data generated with EPIC was synthesized into a functional relationship.

Variable N_{loss} was constructed by adding the amounts of N lost in leaching, surface runoff and sub surface flow obtained from EPIC output (V.W. Benson, personal communication, October 1998) for each soil series under each rainfall scenario. The preliminary analysis suggested that the sum of N lost in these three ways was linear in N applied (Wu et al, 1996). Therefore the following N_{loss} response function was specified:

$$N_{loss} = a + b \times N + u$$

Where N_{loss} = total N lost from leaching, surface runoff and subsurface flow (lb/acre); N = N application rate (lb/acre); u is a random error term; and a, and b are parameters to be estimated by regression.

The above equation was estimated through ordinary least squares procedure (SAS Institute, 1985). The estimated equation was used to predict N loss as a consequence of profit maximizing behavior of farmers under both N application methods. Further, N Loss Difference (NLD) defined as N loss under variable rate N application method minus N loss under uniform rate application method was calculated for each study field under each rainfall scenario

Policy Options to Reduce N Loss

If precision farming promises environmental benefits by reducing N loss into the environment, but farmers hesitate to adopt the technology fearing economic losses, it may be worthwhile for the policy makers to consider policy options that would induce the farmers to adopt the technology. To keep the analysis manageable, the options were analyzed only with respect to a few selected study fields managed with URT.

Subsidizing custom charges

This study examined the impacts of custom subsidies on VRT adoption. The farmers who can not afford VRT at the current custom charges might afford it with subsidies since the additional returns generated with VRT might exceed the subsidized custom charges.

The level of subsidy needed by a farmer to switch from URT to VRT depends upon the level of the expected NRD, which in turn depends upon spatial variability, given yield response functions, input and product prices and custom charges. Since spatial variability differs from field to field, determining exact subsidy amount for each individual field is a cumbersome job.

This study assumes that the policy makers have the necessary information on the yield response and N_{loss} response relationships for the soil types characterizing the fields in a given region and that they are satisfied that VRT on these fields reduces N loss. Since VRT adoption in this study is based on custom services, it is also assumed that the policy makers, through service providers, have an access to the information on how many farmers in the location do not use VRT services. Based on this information, the farmers not using the services are offered certain amount of subsidies, which need not be specific to a particular field. Subsidies are not offered to the current users of the technology since their profit maximizing behavior induces them to continue to use the technology, regardless of whether they get subsidies or not.

Restricting N Application

The other option, which does not cause any burden on the government treasury, but could still motivate the farmers to adopt the technology would be to restrict N use. When N availability is restricted, the precision technology puts each unit of the scarce input to the best possible use from the economic viewpoint unlike URT and, as a result, the difference in the optimum returns between the two application methods gets wider. In other words, the NRD will be larger when N application is restricted compared to when it is unrestricted. This might induce some of the farmers to switch from URT to VRT.

This option also is based on certain assumptions. The policy makers are assumed to have knowledge of yield and N loss response relationships based on which they are convinced that VRT reduces N loss; they are also assumed to have the information about the fields managed with and without VRT. Another assumption made for this analysis is that the policy to reduce N application by a certain percent on the fields managed with URT, can be implemented in coordination with fertilizer dealers. In other words, it is assumed that dealers can keep records of N quantities purchased by individual farmers and restrict the supply when required by the government policy.

The study analyzed this policy option by constraining the farmers using URT to apply not more than 95% of their current N application. The optimization of N application with this policy option can be explained with reference to the same field characterized by Equations 3 – 10. Assume for this illustration that the farmer operating this field under unconstrained N supply finds URT more profitable. This implies that the farmer applies on the field a total amount of N equal to $N^{*}_{Fld} \times (A_{Lr} + A_{Cl} + A_{Mp})$ (For the better comprehension of the entire explanation that follows, please refer to the section 'Accurate weather expectations and economic gains from VRT'). With N restriction, the farmer can apply only up to $0.95 \times N^{*}_{Fld} \times (A_{Lr} + A_{Cl} + A_{Mp})$ for the entire field.

Uniform rate N application

Under URT the N application rate on the field is given by:

$[0.95 \times N^{*}_{Fld} \times (A_{Lr} + A_{Cl} + A_{Mp})] \div (A_{Lr} + A_{Cl} + A_{Mp}) = 0.95 \times N^{*}_{Fld}$.

Variable Rate Application

When N supply is restricted, optimizing N use under VRT requires applying N to each soil type such that the marginal productivity of N is the same everywhere subject to the constraint on N availability. The soil-specific N application rates on the field can be obtained by solving the following equation:

$\beta_{Lr} + 2 \times \gamma_{Lr} \times N_{Lr} = \beta_{Cl} + 2 \times \gamma_{Cl} \times N_{Cl} = \beta_{Mp} + 2 \times \gamma_{Mp} \times N_{Mp}$, such that

$N_{Lr} \times A_{Lr} + N_{Cl} \times A_{Cl} + N_{Mp} \times A_{Mp} = 0.95 \times N^{*}_{Fld} \times (A_{Lr} + A_{Cl} + A_{Mp})$. Notice that the variable N is replaced by N_{Lr} in the marginal physical productivity equation for Loring derived from Equation 3, by N_{Cl} in the marginal physical productivity equation for Collins derived from Equations 5, and by N_{Mp} in the marginal physical productivity equation for Memphis derived from Equation 7. It is done so with a view to distinguishing the solutions for N application rates on Loring, Collins and Memphis soils. Denote the solutions obtained by solving the above equation as $\tilde{N}_{Lr}$, $\tilde{N}_{Cl}$ and $\tilde{N}_{Mp}$ for

Loring, Collins and Memphis soils respectively.

It may be noted that when large amount of N is applied with URT under unconstrained N supply, reducing the total N application by 5% to induce the farmer to adopt VRT might still mean a large amount of N at the disposal of the farmer. As a result, the above soil-specific solutions, $\tilde{N}_{Lr}$, $\tilde{N}_{Cl}$ and $\tilde{N}_{Mp}$, might actually be larger than the corresponding soil-specific solutions obtained for VRT without any constraints on N use, i.e., N^{*}_{Lr}, N^{*}_{Cl} and N^{*}_{Mp}. When a situation of this kind was confronted, the analysis considered smaller application rates of N^{*}_{Lr}, N^{*}_{Cl} and N^{*}_{Mp} instead of $\tilde{N}_{Lr}$, $\tilde{N}_{Cl}$ and $\tilde{N}_{Mp}$ based on economic rationality.

A concern generally expressed about restricting input application in agriculture is that it adversely affects production and returns for the farmers. The study examined if precision application of restricted N quantity could mitigate this concern. In other words, the changes in production and returns when the farmer goes for VRT from URT subsequent to N use restriction were compared with the changes that would occur with N restriction if VRT were not available in the market.

Results

The corn yield responses on Loring soil under rainfall scenario-IV and V did not fit quadratic-plus-plateau model; they could be approximated, instead, by linear-plus-plateau model. Recall that the rainfall scenarios-IV and V meant above-average rainfall for each month and that Loring soil series considered in the analysis had the root restricting fragipan. A partial explanation for the linear yield response may be that the fragipan restricted the availability of soil N to the crop and hence, each additional unit of applied N was efficiently used by the crop, given enough rainfall. Recall also that this analysis required the estimation of field average yield response functions for each rainfall scenario under consideration, for analyzing the outcomes of average rate N application. Estimation of these average functions by combining soil-specific data sets that fitted different functional forms could pose estimation problems. Therefore, to avoid such possibilities, rainfall scenarios-IV and V were dropped from the analysis.

The quadratic-plus-plateau model estimated for Collins and Memphis soils were not statistically different from each other under rainfall scenario-I and II. Therefore, for these two scenarios, a single average function was estimated for these two soils.

Table 2 presents the estimated corn yield response functions for Collins, Memphis and Loring soil series under rainfall scenarios-I, II, and III. The estimated intercepts and linear and quadratic coefficients were statistically significant in all the three scenarios in respect of Collins and Memphis soils and in scenario-II and III in respect of Loring soil. Only the linear coefficient turned out statistically significant in the case of Loring soil under rain scenario-I. The linear and quadratic coefficients for all equations had positive and negative signs respectively, as expected.

The estimated field average response functions for each of the thirty-six fields are not presented here. All these functions had high R^2 values and expected signs for linear and quadratic coefficients. The intercepts and linear and quadratic coefficients were significant in all equations under rainfall scenario-II and III. Under scenario-I, estimated intercepts were insignificant in most cases; linear coefficients were significant in all the

Table 2. Estimated Corn Yield Response Functions for Applied N for Collins, Memphis and Loring Soils under Three Rainfall Scenarios

Soil	Equation	R^2
Collins		
Rainfall Scenario-I	$Y = 19.401 + 1.664 \times N - 0.00391 \times N \times N$ if $N < 212.57$ (5.049)* (0.108) (0.000458) $Y = 196.22$ if $N \geq 212.57$	0.999
Rainfall Scenario-II	$Y = 18.727 + 1.695 \times N - 0.0039 \times N \times N$ if $N < 217.47$ (5.533) (0.116) (0.000481) $Y = 203.05$ if $N \geq 217.47$	0.994
Rainfall Scenario-III	$Y = 22.366 + 1.6 \times N - 0.00542 \times N \times N$ if $N < 147.53$ (2.871) (0.0889) (0.000533) $Y = 140.36$ if $N \geq 147.53$	0.996
Memphis		
Rainfall Scenario-I	$Y = 19.401 + 1.664 \times N - 0.00391 \times N \times N$ if $N < 212.57$ (5.049) (0.108) (0.000458) $Y = 196.22$ if $N \geq 212.57$	0.999
Rainfall Scenario-II	$Y = 18.727 + 1.695 \times N - 0.0039 \times N \times N$ if $N < 217.47$ (5.533) (0.116) (0.000481) $Y = 203.05$ if $N \geq 217.47$	0.994
Rainfall Scenario-III	$Y = 22.094 + 1.677 \times N - 0.00509 \times N \times N$ if $N < 164.76$ (4.401) (0.122) (0.000653) $Y = 160.24$ if $N \geq 164.76$	0.994
Loring		
Rainfall Scenario-I	$Y = 5.674 + 1.639 \times N - 0.00632 \times N \times N$ if $N < 129.61$ (19.130) (0.689) (0.00472) $Y = 111.90$ if $N \geq 129.61$	0.841
Rainfall Scenario-II	$Y = 9.398 + 1.368 \times N - 0.00621 \times N \times N$ if $N < 110.18$ (3.883) (0.165) (0.00133) $Y = 84.76$ if $N \geq 110.18$	0.985
Rainfall Scenario-III	$Y = 10.72 + 0.491 \times N - 0.00361 \times N \times N$ if $N < 67.88$ (0.00408) (0.000299) (0.000004) $Y = 27.37$ if $N \geq 67.88$	0.999

* Numbers in parentheses are asymptotic standard errors. Intercepts and linear and quadratic coefficients were all significant at the $\alpha = 0.10$ level for Collins and Memphis series under all the three rainfall scenarios and for Loring series under scenario-II and III. In the equation for Loring series under scenario-I, only linear coefficient was found significant at the $\alpha = 0.10$ level.

cases; and, quadratic coefficients were significant in most cases.

Table 3 presents the estimated N loss response functions for each soil under each rainfall scenario. The coefficients of N were positive and statistically significant for all the estimated equations. The estimated intercepts, however, were positive and significant only in respect of Collins soil under rainfall scenario-I and II; in other cases, they were insignificant. R^2 values, in general, were high. The overall fit of the regression was significant in each case as suggested by the respective F-values.

VRT Outcomes with Accurate Weather Expectations

Table 4 presents economic and environmental outcomes of VRT adoption, assuming that the farmers correctly predict weather. As the table reveals, when rainfall scenario-I occurred as expected, as many as twenty-eight fields could benefit economically from VRT adoption. The ones on which the technology could not be profitably adopted included fields-8, 15, 21, 26, 30, 33, 35 and 36. The NRD, i.e., the additional returns generated on these eight fields with VRT were less than the custom charges of $300 for VRT services. The table also shows that the above eight fields could not afford VRT under rainfall scenario-II either, while all remaining fields could profitably employ the technology. Under rainfall scenario-III, only five of the above eight fields would incur losses with VRT; the remaining thirty-one fields could increase their returns with precision technology.

According to Table 4, with all the thirty-six farmers expecting either rainfall scenario-I or II, as many as twenty-eight fields would be managed with VRT; the new technology would benefit those fields if the weather expectations were right. Similarly,

Table 3. Estimated N Loss Response Functions for Collins, Memphis and Loring Soils under Rainfall Scenarios – I, II and III

Soil and Rainfall Scenario	Variable	Coefficient	T-Statistic
Collin: Rainfall – I	Intercept	4.2960*	8.05
	N	0.0321*	8.68
	R^2	0.9380	
	F	75.3600	
Collin: Rainfall – II	Intercept	1.8010*	3.78
	N	0.0185*	5.59
	R^2	0.8620	
	F	31.2900	
Collin: Rainfall – III	Intercept	0.4610	1.14
	N	0.0175*	6.24
	R^2	0.8860	
	F	38.9700	
Memphis: Rainfall – I	Intercept	1.9540	1.98
	N	0.0474*	6.93
	R^2	0.9060	
	F	47.9700	
Memphis: Rainfall – II	Intercept	0.8140	1.03
	N	0.0242*	4.42
	R^2	0.7960	
	F	19.5100	
Memphis: Rainfall – III	Intercept	-0.3540	-1.24
	N	0.0170*	8.57
	R^2	0.9360	
	F	73.4500	
Loring: Rainfall – I	Intercept	-7.1440	-0.64
	N	0.4220*	5.42
	R^2	0.8550	
	F	29.3900	
Loring: Rainfall – II	Intercept	-6.7810	-0.84
	N	0.4460*	7.99
	R^2	0.9270	
	F	63.7700	
Loring: Rainfall – III	Intercept	-5.2090	-0.58
	N	0.6020*	9.73
	R^2	0.9500	
	F	94.6100	

* Significant at the $\alpha = 0.05$ level.

Table 4. Net Return Difference (NRD), N Application Difference (NAD) and N Loss Difference (NLD) for Thirty-six Hypothetical Corn Fields under Different Rainfall Scenarios

Field No.	Net Return Difference (NRD)*			N Application Difference (NAD)#			N Loss Difference (NLD)†		
	Rainfall Scenario-I	Rainfall Scenario-II	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-II	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-II	Rainfall Scenario-III
	($)			(lb)					
1	1141.20	1695.31	1444.17	276.80	-905.92	-3418.05	-384.92	-1025.01	-2520.54
2	1406.15	1857.20	1470.06	249.08	-1297.42	-3899.59	-549.80	-1327.69	-2829.64
3	1467.22	1768.55	1353.57	218.45	-1460.13	-3802.31	-654.52	-1447.39	-2751.80
4	1442.44	1535.15	1173.55	411.69	-1478.90	-3468.96	-645.88	-1432.94	-2494.71
5	1269.63	1234.24	965.74	490.73	-1358.19	-2950.17	-615.20	-1303.43	-2112.49
6	973.85	903.66	743.17	460.14	-1148.29	-2315.19	-548.91	-1084.06	-1651.05
7	623.32	577.36	512.54	382.73	-846.56	-1592.06	-427.13	-785.82	-1134.51
8	**273.45**††	**275.38**	**276.60**	245.65	-436.74	-811.78	-245.64	-419.27	-580.70
9	1406.15	1857.20	1372.50	249.08	-1297.42	-3571.67	-558.60	-1331.05	-2621.77
10	1467.22	1768.55	1295.60	218.45	-1460.13	-3626.71	-662.07	-1450.07	-2628.93
11	1442.44	1535.15	1144.64	411.69	-1478.90	-3328.59	-652.52	-1435.02	-2402.75
12	1269.63	1234.24	956.04	490.73	-1358.19	-2845.67	-620.76	-1305.00	-2047.47
13	973.85	903.66	747.51	460.14	-1148.29	-2232.78	-553.22	-1085.16	-1606.11
14	623.32	577.36	526.44	382.73	-846.56	-1551.57	-430.12	-786.51	-1109.72
15	**273.45**	**275.38**	**298.21**	245.65	-436.74	-829.02	-247.22	-419.60	-572.35
16	1467.22	1768.55	1224.41	218.45	-1460.13	-3389.73	-669.62	-1452.75	-2483.42
17	1442.44	1535.15	1102.00	411.69	-1478.90	-3172.58	-659.16	-1437.11	-2305.91
18	1269.63	1234.24	933.72	490.73	-1358.19	-2736.73	-626.32	-1306.57	-1981.31
19	973.85	903.66	738.62	460.14	-1148.29	-2190.72	-557.54	-1086.26	-1568.92
20	623.32	577.36	529.70	382.73	-846.56	-1525.29	-433.11	-787.20	-1086.82
21	**273.45**	**275.38**	310.92	245.65	-436.74	-805.79	-248.80	-419.94	-560.93
22	1442.44	1535.15	1044.96	411.69	-1478.90	-3019.45	-665.80	-1439.19	-2209.93
23	1269.63	1234.24	897.70	490.73	-1358.19	-2648.73	-631.88	-1308.13	-1920.38
24	973.85	903.66	718.98	460.14	-1148.29	-2141.79	-561.85	-1087.36	-1530.38
25	623.32	577.36	522.92	382.73	-846.56	-1501.62	-436.10	-787.88	-1064.25
26	**273.45**	**275.38**	314.45	245.65	-436.74	-795.33	-250.38	-420.28	-550.46
27	1269.63	1234.24	850.46	490.73	-1358.19	-2545.48	-637.43	-1309.70	-1855.59
28	973.85	903.66	689.66	460.14	-1148.29	-2063.38	-566.16	-1088.46	-1486.14
29	623.32	577.36	506.76	382.73	-846.56	-1459.87	-439.09	-788.57	-1039.24
30	**273.45**	**275.38**	309.03	245.65	-436.74	-787.05	-251.96	-420.61	-540.13
31	973.85	903.66	650.57	460.14	-1148.29	-1970.32	-570.47	-1089.57	-1439.05
32	623.32	577.36	481.47	382.73	-846.56	-1401.91	-442.08	-789.26	-1012.02
33	**273.45**	**275.38**	**294.88**	245.65	-436.74	-761.76	-253.53	-420.95	-528.50
34	623.32	577.36	446.46	382.73	-846.56	-1359.82	-445.07	-789.95	-986.92
35	**273.45**	**275.38**	**272.10**	245.65	-436.74	-749.75	-255.11	-421.29	-517.85
36	**273.45**	**275.38**	**241.10**	245.65	-436.74	-712.46	-256.69	-421.62	-505.27

* Total optimum returns above N costs from the entire field under variable rate application minus total optimum returns above N costs from the field under uniform rate application.
# Total optimum N application on the field under variable rate application minus total optimum N application under uniform rate application.
† Total N loss by leaching, surface runoff and subsurface flow from the entire field under variable rate application minus total N loss from the field under uniform rate application.
†† NRD's that are less than the custom charges of $300 are shown in bold numbers; they indicate the cases in which VRT adoption would not be economically feasible.

with all the operators expecting scenario-III, as many as thirty-one fields would switch to VRT and derive economic gains when weather predictions turned out to be right.

The effect of spatial variability on the economic benefits with VRT is clearly revealed by Table 4. Notice how the NRD's and hence, the economic benefits from VRT kept changing as the soil proportions in the study fields changed (Table 1 may be referred to for an idea about the soil proportions in different fields).

It can be noticed from Table 4 that precision farming holds the promise of environmental benefits for all the fields under all the three rainfall scenarios. This is evident from the fact that N Loss Difference (NLD) (total N loss in the form of leaching, surface runoff and subsurface flow under VRT minus total N loss under URT) was negative in all the cases. It is striking to notice that even when N Application Difference (NAD) (total N application under VRT minus total N application under URT) was positive for all the fields under rainfall scenario-I, the corresponding NLD's were invariably negative. The effect of spatial variability may also be noted with respect NLD's.

VRT Outcomes with Inaccurate Weather Expectations

Tables 5, 6, and 7 show the economic as well as environmental outcomes of VRT when the expected weather does not occur.

Table 5 shows whether the operators of the study fields benefited economically or suffered losses when they adopted VRT believing that rainfall scenario-I would occur, but actually scenario-II or III occurred. As shown by the table, when scenario-II occurred, the NRD for all the twenty-eight fields exceeded the custom charge of $300

Table 5. Net Return Difference (NRD), N Application Difference (NAD) and N Loss Difference (NLD) When Farmer Adopts VRT Expecting Rainfall Scenario-I, but Rainfall Scenario-II or III Occurs

Field No#.	Net Return Difference (NRD)*		N Application Difference (NAD)‡		N Loss Difference (NLD)†	
	Rainfall Scenario-II	Rainfall Scenario-III	Rainfall Scenario-II	Rainfall Scenario-III	Rainfall Scenario-II	Rainfall Scenario-III
	............($)............		..............................(lb)..............................			
1	1334.85	**72.64**††	276.80	276.80	-433.91	-600.89
2	1631.23	**65.92**	249.08	249.08	-619.72	-858.79
3	1708.14	**18.70**	218.45	218.45	-737.68	-1022.57
4	1694.23	**-75.25**	411.69	411.69	-734.27	-1021.54
5	1514.33	**-125.34**	490.73	490.73	-702.84	-979.85
6	1190.41	**-119.64**	460.14	460.14	-628.25	-876.59
7	792.16	**-99.51**	382.73	382.73	-489.86	-684.09
9	1631.23	**0.94**	249.08	249.08	-622.99	-858.50
10	1708.14	**-6.69**	218.45	218.45	-740.49	-1022.32
11	1694.23	**-83.20**	411.69	411.69	-736.74	-1021.32
12	1514.33	**-125.79**	490.73	490.73	-704.91	-979.67
13	1190.41	**-119.64**	460.14	460.14	-629.86	-876.45
14	792.16	**-99.51**	382.73	382.73	-490.97	-683.99
16	1708.14	**-31.63**	218.45	218.45	-743.30	-1022.08
17	1694.23	**-91.15**	411.69	411.69	-739.22	-1021.10
18	1514.33	**-126.24**	490.73	490.73	-706.98	-979.49
19	1190.41	**-119.64**	460.14	460.14	-631.47	-876.30
20	792.16	**-99.51**	382.73	382.73	-492.08	-683.89
22	1694.23	**-99.09**	411.69	411.69	-741.69	-1020.88
23	1514.33	**-126.69**	490.73	490.73	-709.05	-979.30
24	1190.41	**-119.64**	460.14	460.14	-633.07	-876.16
25	792.16	**-99.51**	382.73	382.73	-493.20	-683.79
27	1514.33	**-127.14**	490.73	490.73	-711.12	-979.12
28	1190.41	**-119.64**	460.14	460.14	-634.68	-876.02
29	792.16	**-99.51**	382.73	382.73	-494.31	-683.69
31	1190.41	**-119.64**	460.14	460.14	-636.28	-875.88
32	792.16	**-99.51**	382.73	382.73	-495.43	-683.60
34	792.16	**-99.51**	382.73	382.73	-496.54	-683.50

Fields-8, 15, 21, 26, 30, 33, 35 and 36 are not shown, since they will be under URT when rainfall scenario-I is forecast (see Table 4).

* Total optimum returns above N costs from the entire field under variable rate application minus total optimum returns above N costs from the field under uniform rate application.

‡ Total optimum N application on the field under variable rate application minus total optimum N application under uniform rate application.

† Total N loss by leaching, surface runoff and subsurface flow from the entire field under variable rate application minus total N loss from the field under uniform rate application.

†† NRD's that are less than the custom charges of $300 are shown in bold numbers; they indicate the cases in which VRT adoption would not be economically feasible.

Table 6. Net Return Difference (NRD), N Application Difference (NAD) and N Loss Difference (NLD) When Farmer Adopts VRT Expecting Rainfall Scenario-II, but Rainfall Scenario-I or III Occurs

Field No[#].	Net Return Difference (NRD)[*]		N Application Difference (NAD)[‡]		N Loss Difference (NLD)[†]	
	Rainfall Scenario-I	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-III
	............($)............		..............................(lb)...............................			
1	617.40	419.09	-905.92	-905.92	-941.27	-1400.45
2	866.50	431.11	-1297.42	-1297.42	-1218.77	-1814.95
3	893.52	398.44	-1460.13	-1460.13	-1328.07	-1979.26
4	771.88	384.51	-1478.90	-1478.90	-1314.65	-1959.79
5	605.02	353.13	-1358.19	-1358.19	-1195.58	-1782.94
6	420.21	**298.56**	-1148.29	-1148.29	-994.48	-1482.85
7	**248.63**[††]	**220.11**	-846.56	-846.56	-721.05	-1074.82
9	866.50	380.84	-1297.42	-1297.42	-1227.78	-1814.66
10	893.52	392.17	-1460.13	-1460.13	-1335.26	-1979.03
11	771.88	384.51	-1478.90	-1478.90	-1320.25	-1959.61
12	605.02	353.13	-1358.19	-1358.19	-1199.70	-1782.80
13	420.21	**298.56**	-1148.29	-1148.29	-997.44	-1482.75
14	**248.63**	**220.11**	-846.56	-846.56	-722.90	-1074.76
16	893.52	385.90	-1460.13	-1460.13	-1342.46	-1978.79
17	771.88	384.51	-1478.90	-1478.90	-1325.84	-1959.43
18	605.02	353.13	-1358.19	-1358.19	-1203.99	-1782.66
19	420.21	**298.56**	-1148.29	-1148.29	-1000.39	-1482.65
20	**248.63**	**220.11**	-846.56	-846.56	-724.75	-1074.70
22	771.88	384.51	-1478.90	-1478.90	-1331.44	-1959.25
23	605.02	353.13	-1358.19	-1358.19	-1208.2	-1782.52
24	420.21	**298.56**	-1148.29	-1148.29	-1003.35	-1482.56
25	**248.63**	**220.11**	-846.56	-846.56	-726.60	-1074.64
27	605.02	353.13	-1358.19	-1358.19	-1212.41	-1782.39
28	420.21	**298.56**	-1148.29	-1148.29	-1006.31	-1482.46
29	**248.63**	**220.11**	-846.56	-846.56	-728.45	-1074.58
31	420.21	**298.56**	-1148.29	-1148.29	-1009.27	-1482.36
32	**248.63**	**220.11**	-846.56	-846.56	-730.29	-1074.52
34	**248.63**	**220.11**	-846.56	-846.56	-732.14	-1074.46

[#] Fields-8, 15, 21, 26, 30, 33, 35 and 36 are not shown, since they will be under URT when rainfall scenario-II is forecast (see Table 4).

[*] Total optimum returns above N costs from the entire field under variable rate application minus total optimum returns above N costs from the field under uniform rate application.

[‡] Total optimum N application on the field under variable rate application minus total optimum N application under uniform rate application.

[†] Total N loss by leaching, surface runoff and subsurface flow from the entire field under variable rate application minus total N loss from the field under uniform rate application.

[††] NRD's that are less than the custom charges of $300 are shown in bold numbers; they indicate the cases in which VRT adoption would not be economically feasible.

Table 7. Net Return Difference (NRD), N Application Difference (NAD) and N Loss Difference (NLD) When Farmer Adopts VRT Expecting Rainfall Scenario-III, but Rainfall Scenario-I or II Occurs

Field No#.	Net Return Difference (NRD)*		N Application Difference (NAD)‡		N Loss Difference (NLD)†	
	Rainfall Scenario-I	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-III	Rainfall Scenario-I	Rainfall Scenario-III
	.............($).............		...............................(lb)...............................			
1	**-4817.83††**	**-1771.25**	-3418.05	-3418.05	-1743.70	-1860.09
2	**-4432.40**	**-1233.39**	-3899.59	-3899.59	-1956.89	-2087.81
3	**-3680.39**	**-883.68**	-3802.31	-3802.31	-1902.08	-2029.97
4	**-2996.34**	**-662.25**	-3468.96	-3468.96	-1724.23	-1840.22
5	**-2362.75**	**-493.54**	-2950.17	-2950.17	-1459.78	-1558.14
6	**-1760.14**	**-357.37**	-2315.19	-2315.19	-1140.53	-1217.62
7	**-1169.52**	**-233.56**	-1592.06	-1592.06	-782.93	-836.37
9	**-4338.62**	**-1257.95**	-3571.67	-3571.67	-1815.92	-1935.61
10	**-3720.63**	**-922.32**	-3626.71	-3626.71	-1819.20	-1940.14
11	**-3016.07**	**-683.27**	-3328.59	-3328.59	-1661.27	-1772.64
12	**-2375.93**	**-507.11**	-2845.67	-2845.67	-1414.51	-1510.08
13	**-1764.11**	**-360.61**	-2232.78	-2232.78	-1108.28	-1184.05
14	**-1186.26**	**-250.35**	-1551.57	-1551.57	-764.54	-817.62
16	**-3685.58**	**-917.20**	-3389.73	-3389.73	-1720.94	-1833.78
17	**-3015.89**	**-683.68**	-3172.58	-3172.58	-1595.65	-1701.76
18	**-2376.33**	**-507.68**	-2736.73	-2736.73	-1369.22	-1461.48
19	**-1791.71**	**-390.16**	-2190.72	-2190.72	-1083.06	-1156.78
20	**-1208.52**	**-273.76**	-1525.29	-1525.29	-748.47	-800.61
21	**-650.68**	**-184.59**	-805.79	-805.79	-384.10	-412.32
22	**-3011.33**	**-674.84**	-3019.45	-3019.45	-1531.68	-1631.93
23	**-2382.70**	**-515.42**	-2648.73	-2648.73	-1328.76	-1417.18
24	**-1806.90**	**-406.86**	-2141.79	-2141.79	-1057.41	-1128.73
25	**-1226.80**	**-293.41**	-1501.62	-1501.62	-733.28	-784.11
26	**-665.17**	**-199.76**	-795.33	-795.33	-376.62	-404.49
27	**-2368.61**	**-501.86**	-2545.48	-2545.48	-1286.19	-1370.28
28	**-1788.99**	**-388.54**	-2063.38	-2063.38	-1027.94	-1096.56
29	**-1221.14**	**-287.78**	-1459.87	-1459.87	-716.59	-765.91
30	**-675.90**	**-211.36**	-787.06	-787.06	-369.83	-397.00
31	**-1748.45**	**-346.65**	-1970.32	-1970.32	-997.00	-1062.51
32	**-1191.49**	**-256.94**	-1401.91	-1401.91	-698.71	-746.24
34	**-1169.86**	**-235.34**	-1359.82	-1359.82	-683.29	-728.48

Fields-8, 15, 33, 35 and 36 are not shown, since they will be under URT when rainfall scenario-III is forecast (see Table 4).

* Total optimum returns above N costs from the entire field under variable rate application minus total optimum returns above N costs from the field under uniform rate application.

‡ Total optimum N application on the field under variable rate application minus total optimum N application under uniform rate application.

† Total N loss by leaching, surface runoff and subsurface flow from the entire field under variable rate application minus total N loss from the field under uniform rate application.

†† NRD's that are less than the custom charges of $300 are shown in bold numbers; they indicate the cases in which VRT adoption would not be economically feasible.

and hence, the farmers operating these fields were better off with VRT despite the wrong weather expectations. However, all the twenty-eight farmers suffered losses when the rain scenario-III occurred instead of scenario-I.

Table 6 shows whether VRT helped the farmers or adversely affected their economic interests when they chose to apply N at variable rates expecting rain scenario-II, but scenario-I or III occurred. As revealed by the table, a majority of the farmers who chose VRT expecting scenario-II still benefited from the technology despite the wrong weather expectations, while some were adversely affected since the NRD was not enough to offset custom charges.

Table 7 presents the most striking effects of going for VRT, when weather predictions turn out to be wrong. None of the thirty-one farmers who implemented VRT expecting rain scenario-III could gain from the technology when they were wrong in their expectations. In fact, whether scenario-I occurred or scenario-II, the additional returns generated with VRT were negative for all the fields. Especially, when scenario-I occurred, the negative returns were of high magnitude in several cases. For example, the returns obtained by the farmer operating field-1 were $4800 less as compared to the returns under URT. In addition, the farmer had to pay $300 as custom charges. Thus, the farmer suffered a total loss of $5100 by adopting VRT as a consequence of wrong foresight about weather.

It is thus clear from Tables 5 – 7 that right weather predictions are important in precision farming. In respect of several fields, the analysis revealed that wrong weather expectations could make VRT much worse than URT, from the economic viewpoint.

Farmers seeking to try the new technology need to formulate well-informed weather expectations.

Tables 5 – 7 show the potential of precision farming in reducing N loss into the environment, even when the weather expectations go wrong. N losses were less with VRT virtually in all the cases shown in the tables.

The Impacts of Policy Measures to Promote VRT

Irrespective of the weather scenario expected, there were at least some farmers who would not voluntarily adopt VRT, though the new technology on their fields could considerably reduce N loss (see Table 4). This section presents the outcomes of two policy measures, subsidizing custom charges and restricting N use, for inducing such farmers to adopt VRT and help reduce N loss. The analysis was carried out with respect to the fields-8, 15, 33, 35, and 36, which were managed with URT regardless of the weather scenario expected.

For analyzing the above five fields, the NRD's and the response functions relating to rain scenario-III were used. The reason for choosing scenario-III can be explained looking at the proportions of the three soil types on these five fields (see Table 1). Each of these five fields had 10% Loring soil implying remaining 90% field area was occupied by Collins and Memphis series. However, recall that a single response function represented both Collins and Memphis soils under rainfall scenario-II and III. In other words, given that Loring occupied 10% area, the varying distribution of the remaining field area between Collins and Memphis on these five fields did not make any difference in NRD, under the two rainfall scenarios. It also meant the same amount of N application on these fields. For scenario-III, however, each response function was different and policy analysis based on this scenario would be more diverse and interesting.

<u>Subsidizing custom charges</u>

The field-36 generated the smallest NRD of $241.10 with VRT. The farmer operating this field needed a subsidy of at least $59 in custom charges before he/she could adopt VRT. Suppose, for example, the custom subsidy offered to each of the five farmers equaled this amount. In that case, all the five farmers using URT would go for VRT. The total cost for the government would be around $300. All the fields switching to VRT would help reduce N loss into the environment (see Table 4).

<u>Restricted N application</u>

For this policy analysis, the five farmers following URT under rain scenario-III were constrained to apply not more than 95% of the N amount currently applied. Table 8 presents the results. Subsequent to N restriction, the NRD increased to more than $300 in all the five cases making VRT more attractive. Adoption of VRT reduced N loss considerably on all the fields. For example, on field-8, total N loss decreased from 1070 lb to 490 lb; on field- 36, it decreased from around 1040 lb to 530 lb.

The table also shows how the effects of N restriction could be different with precision application and uniform rate application. Corn output, as expected, fell when N application was restricted and the restricted quantity was applied uniformly, compared to the output produced with uniform rate application under the conditions of unconstrained N supply. The striking result, however, was that corn production actually increased with N restriction, when the restricted quantity was precisely applied. This was true of all the

Table 8. Effects of Restricting N Use on Total Production, Returns and N Loss in Respect of Five Fields Managed with URT When Rain Scenario-III is Expected

Field No.	Constraints on N Application	NRD[†]	N Application Method Adopted	Production under the Adopted Method	Optimum Returns under the Adopted Method[‡]	N Loss under the Adopted Method	N Loss Difference (NLD)[#]
		($)		(bu)	($)	(lb)	(lb)
8	i. No constraints	276.60	URT[*]	14428.92	36304.88	1072.50	-580.70
	ii. Max. of 95% of Current N Use when VRT Is Available	363.36	VRT	14452.41	36281.48	491.81	-523.26
	iii. Maximum of 95% of current N Use When VRT Is Not Available	NA[**]	URT	14326.98	36218.13	1015.10	NA
	Change in Production and Returns Due to N Restriction:						
	When VRT Is Available [(ii) – (i)]	NA	NA	23.49	-23.40	NA	NA
	When VRT Is Not Available [(iii) – (i)]	NA	NA	-101.94	-86.75	NA	NA
15	i. No constraints	298.21	URT	14225.27	35775.32	1070.19	-572.35
	ii. Max. of 95% of Current N Use when VRT Is Available	375.65	VRT	14254.90	35773.53	497.83	-515.44
	iii. Maximum of 95% of current N Use When VRT Is Not Available	NA	URT	14127.37	35697.88	1013.28	NA
	Change in Production and Returns Due to N Restriction:						
	When VRT Is Available [(ii) – (i)]	NA	NA	29.63	-1.79	NA	NA
	When VRT Is Not Available [(iii) – (i)]	NA	NA	-97.90	-77.44	NA	NA
33	i. No constraints	294.88	URT	13430.16	33746.84	1050.44	-528.50
	ii. Max. of 95% of Current N Use when VRT Is Available	365.64	VRT	13464.86	33741.71	521.94	-474.19
	iii. Maximum of 95% of current N Use When VRT Is Not Available	NA	URT	13338.03	33676.07	996.13	NA
	Change in Production and Returns Due to N Restriction:						
	When VRT Is Available [(ii) – (i)]	NA	NA	34.70	-5.13	NA	NA
	When VRT Is Not Available [(iii) – (i)]	NA	NA	-92.13	-70.77	NA	NA
35	i. No constraints	272.10	URT	13239.69	33261.65	1045.82	-517.85
	ii. Max. of 95% of Current N Use when VRT Is Available	341.36	VRT	13267.35	33233.76	527.97	-464.25
	iii. Maximum of 95% of current N Use When VRT Is Not Available	NA	URT	13149.02	33192.40	992.22	NA
	Change in Production and Returns Due to N Restriction:						
	When VRT Is Available [(ii) – (i)]	NA	NA	27.66	-27.89	NA	NA
	When VRT Is Not Available [(iii) – (i)]	NA	NA	-90.67	-69.25	NA	NA
36	i. No constraints	241.10	URT	13049.82	32784.70	1039.27	-505.27
	ii. Max. of 95% of Current N Use when VRT Is Available	314.01	VRT	13069.84	32725.80	534.00	-452.40
	iii. Maximum of 95% of current N Use When VRT Is Not Available	NA	URT	12958.77	32711.80	986.39	NA
	Change in Production and Returns Due to N Restriction:						
	When VRT Is Available [(ii) – (i)]	NA	NA	20.02	-58.90	NA	NA
	When VRT Is Not Available [(iii) – (i)]	NA	NA	-91.05	-72.90	NA	NA

[†] Net Return Difference, i.e., total optimum returns above N costs from the entire field under variable rate application minus total optimum returns above N costs from the field under uniform rate application.
[*] URT and VRT refer to uniform rate technology and variable rate technology, respectively. VRT is adopted when NRD > custom charges ($300)
[‡] Refer to the returns above N costs when URT is adopted and, returns above N costs as well as custom charges of $300 when VRT is adopted.
[#] Total N loss by leaching, surface runoff and subsurface flow from the entire field under variable rate application minus total N loss from the field under uniform rate application; absolute numbers indicate N loss avoided, if the current method is VRT and N loss that can be potentially avoided with VRT, if the current method is URT.
[**] Not Applicable.

five cases considered. For example, field-8 produced 102 bushels less when N was limited and it was applied uniformly, compared to when no limit was placed on N. However, when the restricted N amount was applied at variable rates, production actually increased by more than 20 bushels.

The table also shows that the returns fell as expected subsequent to constraints on N application, but the reductions in returns were much less when the restricted quantity was applied precisely. For field-8, restricting N application meant a fall in returns by more than $85 assuming VRT was not available and the farmer was forced to follow URT only; with VRT available, the farmer found precision application more attractive and the returns were reduced by less than $25.

Conclusions

This simulation study investigated economic and environmental effects of precision farming, assuming that the technology is adopted by custom hiring the VRT services from the farm supply sector. For analyzing the impacts of spatial variability on the outcomes of technology adoption, a total of thirty-eight hypothetical fields were created by changing the proportions of three important soil series of West Tennessee, suited to growing corn. Further, to investigate the effects of weather predictions on the economic benefits from the technology, different rainfall scenarios were created.

The Environmental Policy Integrated Climate (EPIC) simulator was used to estimate corn yield and N loss response functions for applied N. The analysis was conducted assuming that farmers apply N in accordance with their profit-maximizing behavior, whether they follow URT or VRT.

The results revealed that farming decision supported by correct weather expectations was an important factor in determining the economic gains from the technology adoption. Most of the study fields benefited economically from VRT adoption, when the rainfall pattern occurred as predicted. The results also showed considerable environmental benefits in terms of reduced N loss from leaching, subsurface flow and surface runoff. When rainfall occurrence was different from the pattern predicted, URT was found more profitable than VRT in several cases. This particular observation suggested a need on the part of the farmers to make more informed and accurate predictions about the weather patterns so their economic interests would not be at stake with the new technology.

Spatial variability influenced considerably the magnitude of additional returns generated with the new technology and the extent to which N loss was reduced.

The study analyzed two policy options to motivate the farmers to go for precision farming and reduce thereby N loading into the environment: subsidizing custom charges and restricting N application. When N application was restricted, the additional returns generated with VRT went up and exceeded custom charges inducing the farmers to adopt VRT.

To sum up, the results of the study highlighted the importance of more accurate weather predictions so the farmers could derive expected economic benefits from VRT adoption. Given the potential of precision farming to benefit environment by reducing infiltration of nutrients into ground water, policy makers could consider subsidizing custom charges or restricting input use to increase technology adoption. More importantly, according to the results, the concern that input use restriction reduces production and farm incomes need not hold to the same extent in the world where VRT is available. With farmers having access to VRT services, restricting input application has the potential to motivate the farmers to adopt the technology and reduce environmental harms, without much adverse effects on farm incomes.

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Part 5: Summary

Summary

This study analyzed the role of within-field variability in precision farming from both economic and environmental viewpoints. The specific objectives of the study were (i) to illustrate *analytically* how within-field variability influences the economic outcomes of alternative sampling intensities and, thereby, the choice of most economical sampling scheme, (ii) to illustrate the role of spatial break-even variability proportions in the fields with two or more land types, (iii) to illustrate the role of weather expectations in precision farming, (iv) to test the hypothesis that precision farming holds the promise of environmental benefits, and (v) to examine policy options to motivate farmers to adopt precision farming if the new technology is found to reduce environmental degradation.

The study was based on the assumption that farmers' input application decisions reflected their profit-maximizing behavior. The study assumed VRT adoption based on custom services hired from the farm supply sector. The first two objectives were accomplished using hypothetical corn yield response functions. The last three objectives were accomplished with the help of the Environmental Policy Integrated Climate (EPIC) crop growth simulator.

The results indicated highly significant role of within-field variability in precision farming. The Net Return Difference (NRD) realized with a given sampling intensity increased with the degree of within-field variability. Further, higher intensity sampling was found economically optimum for the fields with higher variability. According to the results, farmers need to plan their sampling schemes based on their prior knowledge of

within-field variability. This prior knowledge might relate to varying soil type, slope, soil depth as well as yield patterns shown by yield monitors.

Farmers need not necessarily go for grid sampling when practicing VRT. They might want to apply inputs at spatially variable rates to different land types identified according to their physical attributes and expected yield responses to applied inputs. In such cases, the relative proportions of land types on the field greatly influence the economic outcomes of technology adoption. Therefore, farmers need to know what land mix in the field could assure them enough NRD with VRT so they could at least cover the custom charges. This study developed a method to determine the minimum spatial variability, referred to as *spatial break-even variability*, required for VRT adoption on the fields with two or more land types so the farmers would not incur financial losses. The method developed was flexible in that the changes in input and product prices and custom charges could be easily incorporated into the framework for calculating the break-even variability proportions.

The analysis also investigated environmental benefits from VRT adoption using the Environmental Policy Integrated Climate (EPIC) crop growth model. The results indicated potential of the new technology to reduce environmental harms due to N loss into the environment. The results also highlighted the importance of accurate weather expectations in precision farming. Given the environmental benefits from variable rate application of N, policy measures to promote technology adoption were suggested by the analysis. They included subsidizing custom charges and restricting N application. When N application was restricted, VRT applied each unit of the scarce input in most profitable way and induced the farmers to turn to precision farming and help reduce environmental contamination. The results indicated that the adverse effect on farm income due to restricting N application was much less with VRT than with conventional uniform rate application. Interestingly, corn production with precise application of restricted N quantity was more than the quantity produced with uniform rate application under the conditions of unconstrained N supply.

Vita

Shivakumar B. Mahajanashetti was born in Benakanahalli, Bijapur district, Karnataka State, India, on August 1, 1958. He completed his primary education in that village in 1972. His secondary school education was completed at V.B. Darbar High school, Bijapur, in 1975 and Pre-University Course at P.D.J. Junior College, Bijapur, in June 1978.

Mr. Mahajanashetti entered College of Agriculture, Dharwad, India, in August 1978 for pursuing undergraduate studies in Agricultural Marketing and Cooperation and earned B.S. degree in 1982. He earned master's degree in Agricultural Economics from the same institute in 1987. He served College of Agriculture, Dharwad as an instructor in Agricultural Marketing and Cooperation from November 1988 through July 1994.

In August 1994, Mr. Mahajanashetti joined the University of Tennessee, Knoxville for pursuing doctoral studies in Agricultural Economics. He earned Doctor of Philosophy degree in May 1998.