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Adding value to spatially managed inputs by understanding site-specific yield response

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Abstract

Many mechanized crop producers and agribusinesses are fascinated with precision agriculture technology, but adoption has lagged behind the expectations. Among the reasons for slow adoption of precision agriculture technology is that initial users focused excessively on in-field benefits from variable-rate fertilizer application using regional average fertilizer recommendations. This article illustrates how greater use of site-specific crop response information can improve variable rate input application recommendations.

Precision agriculture is spatial information technology applied to agriculture. The technologies include global position systems (GPS), geographic information systems (GIS), yield monitoring sensors, and computer controlled within-field variable rate application (VRA) equipment. Experimentation with these technologies is occurring everywhere there is large scale mechanized agriculture. Commercial use has been greatest in the US, where 43% of farm retailers offered VRA services in 2001. Except for certain high-value crops like sugar beet, farmer adoption of VRA has been modest. The farm level profitability of VRA continues to be questionable for bulk commodity crops.

The theoretical model and illustration presented here suggest that VRA fertilization has not yet reached its profitability potential. Most VRA field trials to date have relied upon existing state-wide or regional input rate recommendations. Unobserved soil characteristics can potentially interact with an input to make its effect on yield vary site-specifically within fields. Failure to use site-specific response functions for VRA applications may lead to a misallocation of inputs just as great as that which results from using uniform applications instead of VRA.

Agricultural economists have a long history of estimating output response to input applications. Several have started to develop tools to estimate site-specific responses from yield monitor and other precision agriculture data. Likewise, agricultural economists have developed an important body of research results on information value based on managing variability—typically in temporal settings. With these tools, a major potential exists to develop further benefits from precision agriculture technologies that permit truly spatially tailored input applications.

JEL classification: Q12; Q16

Keywords: Precision agriculture; Site-specific; Response analysis; Variable rate; Fertilizer

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1. Introduction

Global positioning systems (GPS) and sensors are turning the data-poor agricultural production sector into a data-rich environment. Farmers have always known that crop yields vary spatially. But until the early 1990s the technology of commercial farm equipment did not permit much in the way of spatial management, and gathering data on spatial variability of yields or farm land characteristics for the purpose of fine-tuning management was too expensive. Because of this expense, generation of detailed crop production data was limited to small plot trials, mainly on experiment stations. One-size-fits-all extension recommendations based on these small plots were extrapolated over large areas. But in the 1990s, the civilian use of GPS and availability of low cost computers made spatially-related management technologically feasible, and created an explosion of agricultural data with locational attributes.

It will be argued in this paper that the way in which crop input application recommendations are developed has not caught up with the technological progress that has made spatial management technologically feasible. Thus, at this point in time there remains a disconnection between the regional-scale recommendations for input management put out by extension services, and the detailed spatial data that are now inexpensively recoverable with the newest technologies. This disconnection raises important questions about whether more spatially tailored input recommendations could add value for crop producers. The purpose of this article is to raise these questions explicitly, and to begin to address them. In particular, this paper aims: (1) to summarize economic research on variable rate input use, including diagnosis of adoption constraints; (2) to restate the crop production economics problem in spatial terms; and (3) to illustrate how incorporating site characteristics into variable rate application (VRA) fertilization recommendations can make variable rate farming more profitable and spatial field data more valuable. Accomplishing these objectives leads to the conclusion that the way in which agronomists and agricultural economists recommend input application rates to farmers should change radically to make better use of spatial input management technology in both production and data collection.

2. Background and hypothesis

Use of GPS, geographical information systems (GIS), electronic sensors and other spatial information technology in farming is often labeled "precision agriculture." Though the technology has wide implications for marketing, risk management, logistics and other whole farm information system issues (Swinton and Lowenberg-DeBoer, 1998), its initial use has been on intrafield management of crop inputs by varying application rates within fields. Experimentation with precision agriculture technology is occurring throughout the world wherever farming is mechanized. The technology is being used commercially in the US, Canada, Argentina, Brazil, South Africa and in most western European countries (Norton and Swinton, 2002; Swinton and Lowenberg-DeBoer, 2001). (A fuller description of precision agriculture technology and potential uses can be found in Lowenberg-DeBoer and Erickson (2000) and Morgan and Ess (1997).)

The crop GIS has many layers. From an economic perspective, the yield layer is the integrator of all the factors that influence crop growth, but many factors and their interactions influence that yield. Much of the early interest in spatial crop growth variability came from soil scientists. The soils layers include soil test results on macro- and micronutrients, organic matter level and soil physical characteristics. One of the first observations from yield maps was that production seemed closely linked to water availability and movement. This triggered an interest in topography, micro-climates and drainage layers. Since the 1970s, there have been attempts to use remote sensing images in crop production. Including aerial and satellite images in a crop GIS potentially provides low cost information on crop growth and plant population.

Spatial management of seasonal inputs is made possible by VRA controllers. These controllers can modify rate of input flow or switch input source (e.g. between seed or fertilizer types) in response to computer signals as farm equipment moves through a field. VRA equipment makes it possible to implement site-specific input control in response to GIS records of input needs and GPS location data. This site-specific control of inputs has two possible benefits. First, it allows farmers to tailor their input application rates to the varying yield response characteristics in different parts of a field. Second, it allows for inexpensive gathering of site-specific data, which can provide the farmer desiring to farm using VRA with valuable information.

In Section 3, a literature review is presented to argue that economic performance of VRA in general has been poor. A variety of economic and technical reasons are presented to explain why most VRA has been implemented with an estimate of input needs based on whole field information. This observation leads to the key hypothesis, illustrated in Section 5 using the theoretical framework developed in Section 4, which is that the poor economic performance of VRA has come about chiefly because information on the spatial variability of crop response has not been used sufficiently in developing input recommendations (Swinton and Lowenberg-DeBoer, 1998).

3. Economic research on adoption of VRA

In 2001, about 46% of all farm retailers in the US offered some type of intensive soil sampling services, most commonly on a 1 ha (2.5 acre) grid basis (Whipker and Akridge, 2001). About one-third of US retailers offered some type of computer-controlled fertilizer VRA in the 2001 crop season. In the Midwest, almost 43% of retailers offered VRA in 2001. Computer-controlled VRA services in the US were introduced in the late 1980s, and grew rapidly in the 1990s, but sales have been flat since 1999.

For some higher value specialty crops, like sugar beets, usage of variable rate nutrient spreading is quite high. Grower surveys indicate that in 1996 about 25% of the beet acres in the Red River Valley of North Dakota and Minnesota were grid soil sampled and had nitrogen applied at a variable rate. In 1999, variable rate nitrogen was used on about 40% of the sugar beet acreage in the two states (Franzen, 2000).

For bulk commodities (e.g. corn, soybeans and wheat), the rate of intensive soil sampling and variable rate application has been substantially lower than dealer service offerings would indicate. Khanna et al. (1999) showed that about 14% of farmers in Illinois, Iowa, Indiana and Wisconsin used some GPS soil sampling in 1997 and about 12% some variable rate fertilizer in 1997. USDA data from 1998 show that nation-wide in the US, about 2% of all farms were using grid soil sampling or VRA (Daberkow and McBride, 2000), but adoption was higher for grain and oilseed producers. The 1998 USDA data shows that 7% of grain and oilseed producers used grid soil sampling and 6% used VRA. A 1999 Ohio survey showed that about 8% of farmers had done some GPS soil sampling and about 7% some VRA of fertilizer or lime (Batte, 2001).

Many US producers of bulk commodities (corn, soybeans and wheat) are fascinated by the idea of site-specific management of soil fertility. It is an intuitively appealing concept, but has been plagued by continued questions about the profitability of the practice. The response of many growers has been to enroll part of their acreage in one of the site-specific soil management programs offered by fertilizer retailers. For many farmers this is a low cost way to learn about precision farming without long-term investment in equipment.

In western Europe, Latin America and Australia there is experimentation with VRA, but relatively little commercial use (Norton and Swinton, 2002). In Latin America and Australia the high cost of soil sampling limits the intensive soil sampling that is currently the basis of VRA decisions. In western Europe VRA seems to be driven mainly by environmental concern and regulation. In a 1997 mail survey of 90 crop farmers in Great Britain, Fountas (1998) found that 7% used VRA and 12% used spatially referenced soil sampling and mapping.

Use of variable rate planting and variable rate pesticide application is more scattered than is use of variable rate fertilizer application. Khanna et al. (1999) found that in 1997 about 2.1% of farmers in Illinois, Iowa, Wisconsin and Indiana practiced variable rate pesticide application, and about 1% did variable rate seeding. Daberkow and McBride (2000) show that about 1.7% of US producers used variable rate pesticide application in 1998, and the use of variable rate seeding was less than 1% of farmers.

3.1. VRA profitability in field trials

The data cited above indicate that while for some higher value crops, VRA seems to have been adopted on a systematic and wide scale, for the great majority of crops, VRA adoption rates remain quite low. An obvious candidate to explain low adoption rates is the possibility that profit rates from VRA are low. Most economic studies of precision agriculture technology have focused on VRA of fertilizer because that was the first technology to be commercialized and it was also the one on which the most data was available for economic analysis. The published results on profitability of VR nutrient applications can be difficult to interpret, due to differences in experimental design and assumptions about included costs. Lambert and Lowenberg-DeBoer (2000) reviewed 108 studies of precision agricultural profitability. Some 63% report profits, but many of those omit important costs, make unrealistic yield advantage estimates, or use simulation methods that may underestimate non-treatment effects. Partial budgets on VR fertilizer application are driven by three elements: (1) increased cost of soil sampling information and VRA; (2) change in cost of fertilizer applied; and (3) change in revenue due to crop yield. The added information cost is central, yet it is omitted from some studies.

Swinton and Lowenberg-DeBoer (1998) examined profitability results from nine university field research studies of VRA fertilization (Table 1). They applied standard minimum cost assumptions to all studies where selected cost items had been omitted. They found that the value of crop yield gains was especially important. High-value crops that responded to VRA of fertilizer tended to do so more profitably than low-value crops, because the yield gains were worth more. VRA of fertilizer on wheat and barley was nowhere profitable, the results for corn were mixed, and VRA fertilizer on sugar beet was profitable. By contrast, cost savings from reduced fertilizer application were much less important. The fertilizer inputs being managed are fairly low cost and only one study managed more than two of them. Given that soil testing is fairly costly, most of the crops are of fairly low value, and macronutrient fertilizers are relatively cheap, the cost of over-fertilizing is fairly low.

3.2. *VRA profitability in simulation studies*

There is a similar group of studies using crop growth simulation to evaluate site-specific soil nutrient management. Lowenberg-DeBoer and Swinton (1997) review the simulation studies through 1997. Simulation studies that have appeared after 1997 include: Thirkawala et al. (1999), Babcock and Pautsch (1998) and English et al. (1999). Like field studies, the simulation studies give mixed profitability results for VRA fertilization, but they are more likely to show VRA profitability because they do not always include other yield limiting factors. For example, intensive soil sampling may show areas of low phosphorus in a field. Simulation may suggest a yield increase with VRA of phosphorus. The reality may be that these are areas in which water holding capacity is the most limiting factor and increasing phosphorous has little yield benefit.

3.3. *Other VRA input technologies*

Scattered studies have dealt with the economics of VRA of inputs other than fertilizer. In on-farm experiments Barnhisel et al. (1996) showed that variable rate plant populations can be profitable in the Kentucky karst landscape, which are characterized by wide variation in yield potential. Lowenberg-DeBoer (1998) showed when management zones are determined by yield potential, variable rate seeding for corn is profitable only when some parts of the field have potentials below 6.3 Mg/ha. Bullock et al. (1998) analyzed small plot data from 1987 to 1996 and found that there may be small yield gains when plant population is varied by soil type, but the cost of determining optimal plant population by soil type probably exceeds the benefit in most cases. Bongiovanni and Lowenberg-DeBoer (2000a) used a simulation model to analyze the profit potential of VRA of lime in Indiana. They found that VRA of lime was profitable under a wide range of circumstances, largely due to the fact that the optimal pH range is relatively narrow and there are negative effects of over-liming (e.g. micronutrient tie up, increased damage from certain soil applied herbicides).

3.4. *Integrated VRA systems*

In principle, precision management of multiple inputs can provide greater profitability than managing each input separately for two reasons. First, interactions between inputs can be fine-tuned. Second, data collection, analysis and implementation steps can be combined for some inputs. The interaction of the right corn hybrid at the best population for that hybrid with the profit maximizing nitrogen rate for that hybrid and population, can yield better and may be more profitable than if each input were optimized separately. One example of combining steps occurs in soil

Table 1
Profitability conclusions from nine university field research studies[a]

Study	Crop	Inputs	Grid cell (ha)	Percentage of site-years where precision profitable	Treatment of annual sampling and VRA costs (plus adjustments made to original data)
Anonymous (1996)	Sugar beet	N	1.11	100% (2 of 2)	Sampling and VRA cost of US$ 54.34/ha included
Carr et al. (1991)	Wheat, barley	N, P, K	Soil map unit (1.21 ha assumed)	20% (1 of 5)	Sampling and VRA cost of US$ 9.88/ha added
Fiez et al., 1994	Wheat	N	Plot trials (1.21 ha assumed)		Sampling and VRA cost of US$ 9.88/ha added
Lowenberg-DeBoer and Aghib (1999)	Corn	P, K	1.21	42% (5 of 12) for grids, 50% (6 of 12) for soil type	Sampling, VRA and data management cost of US$ 24.33/ha included
Schnitkey et al. (1996)	Corn, soybean	P, K	1.01	83% (15 of 18)	Sampling and VRA cost of US$ 9.88/ha included
Snyder et al. (1996)	Corn (irrelevant)	N	0.30	50% (2 of 4)	Sampling, VRA and data management cost of US$ 42.76/ha included
Wibawa et al. (1993)	Wheat, barley	N, P	Soil map unit (1.21 ha assumed)	0% (0 of 2)	VRA cost of US$ 7.41/ha substitutes for US$ 2.47/ha
Wollenhaupt and Buchholz (1993)	Corn (Missouri data only)	P, K	1.01	50% (1 of 2)	Sampling and VRA cost of US$ 8.15/ha included
Wollenhaupt and Wolkowski (1994)	Corn	P, K	0.85	100% (5 of 5) grid points, 0% (0 of 2) cell average	VRA cost of US$ 7.41/ha substitutes for US$ 3.56/ha

Source: Swinton and Lowenberg-DeBoer (1998).
[a] The studies compared whole-field average with VRA, with fertilizer rate determined on or prior to date of application (minimum grid cell areas of 1.24 ha).

sampling. The labor required to do grid soil sampling is the same whether that sample is tested for only pH, or also tested for phosphorus, potassium, cation exchange capacity (CEC), and other characteristics. VRA costs will be lower if soil sampling costs can be spread over multiple inputs.

There are no truly integrated precision farming systems, but evidence from the Sauder farm trials (Finck, 1998) provides support for the idea that systems that manage multiple inputs are more profitable. These trials integrated variable rate management of nitrogen, phosphorus and potassium with planting rate on a 526 ha farm producing a balanced corn–soybean rotation in central Illinois. (The experimentation "cost" was treated as a sunk cost at the time when the Sauder VRT trials where conducted.) Over 3 years the average benefit from the GPS-based management for both corn and soybeans was US$ 34.35/ha. The experimental design did not allow researchers to identify which parts of the system contributed most to the benefit, but it was clear that a 0.9 Mg/ha increase in average corn yields played an important role. This is one of the only studies that have shown a statistically significant impact of site-specific management on yields.

In addition to being more integrated, the Sauder farm trials differed from virtually all other precision farming research in that the producer had conducted on-farm research to determine optimal nitrogen rates and corn plant populations on his soils and his management before starting VRA. A key hypothesis is that the impressive agronomic and economic performance in the Sauder trials is linked in part to use of site-specific response information, instead of relying on regional recommendations.

4. A model of spatial profit optimization

Unlike the Sauder farm, contemporary VRA fertilization in the US usually works from recommendations that are based on regional average crop growth. Given the ability to gather spatial agronomic data and apply inputs spatially with VRA, the challenge is to decide how much of each input to apply in order to meet the objective of maximizing the decision maker's satisfaction, which we will proxy here with the profit function $\pi(\cdot)$. To make explicit the issues at hand, a theoretical model of spatial profit optimization is presented.

For a crop producer it is assumed that $\pi(\cdot)$ is increasing in crop yield and that crop yield $f(\cdot)$ can be described as a function of managed variable inputs (x), unmanageable stochastic inputs (z—notably weather), and unmanageable but non-stochastic site characteristics (c). The site characteristics argument distinguishes this spatially manageable yield function (Bullock et al., 1998; Bullock and Bullock, 2000) from those previously used to develop input recommendations (Heady and Dillon, 1961; Dillon and Anderson, 1990).

Agronomic research has tended to find that plant nutrients increase crop yield up to some maximum level beyond which they may plateau or decline. Where pests are present, this pattern is also true of damage-control inputs like pesticides. So it is reasonable to expect $f(x, z, c)$ to be locally concave at economic levels of x, though it may have an increasing marginal product and be locally convex at low levels of x. Second, the arguments of the yield function typically interact (e.g. fertilizer, soil characteristics and rainfall), so the yield function is non-separable in these traits, especially x and c.

Using a variant of the classic profit maximization problem adapted to spatial management by Lowenberg-DeBoer and Boehlje (1997) and Bullock and Bullock (2000), the basic spatial management optimization problem can be written as:

$$\max_{x_{i,j}} \pi = \sum_{i}^{n}\sum_{j}^{m} p y_{i,j} - w x_{i,j} - g - v - F,$$

$$\text{such that } y_{i,j} = f(x_{i,j}, c_{i,j}, z) \tag{1}$$

where p is output price, w is a vector of input prices, y is yield, x is a vector of managed inputs, c is a vector of site characteristics, and z is a vector of uncontrollable factors that are variable by site. The last three terms in the objective function are costs: g are quasi-fixed costs for data collection and management, v are quasi-fixed costs for VRA technology, and F are other fixed costs. Subscripts i and j index variables to rectangular cells in a Cartesian plane, where i is the latitude of a cell's center, and j is the longitude. Weather variables z are assumed not to vary within the farmer's field, and therefore do not carry the spatial subscripts i, j.

Central to developing the decision tool is the empirical task of finding parameters for manageable inputs in the yield function $y_{i,j} = f(x_{i,j}, c_{i,j}, z)$. The most common approach to parameterizing a yield function is statistical estimation. Field data are required that include variability in all of the variables serving as arguments in the yield function. Unfortunately, in many cases the field characteristic variables $c_{i,j}$ may be non-observable. In this case it is not possible to estimate the "meta" yield response function $f(x, c, z)$. However, it may still be possible, without observing $c_{i,j}$, to estimate a "site-specific" yield response function $f_{i,j}(x_{i,j}, z) \equiv f(x_{i,j}, c_{i,z}, z)$ for a small piece of land. This implies conducting on-farm experiments to estimate site-specific yield response functions. Locally, site-specific yield response functions can embody fixed effects that explicity model the activity of site characteristic variables omitted from previous recommendations. Omitting any relevant variable may introduce bias if there exists correlation between included and omitted variables (Griliches, 1957; Greene, 1990, p. 259).

The existing research base for agronomic input recommendations was developed long before spatial data management technologies came into being. The consequences may partially explain the findings that VRA input management tends to be unprofitable on US field crops (Swinton and Lowenberg-DeBoer, 1998). The following section illustrates how omission of relevant site characteristic variables can influence parameter estimates as well as the value of site sampling information.

5. An illustration of information value from spatial crop yield response data

A heuristic simulation was developed to illustrate the difference in the profitability of VRA technology used under regional yield response information versus VRA technology used with site-specific yield response information. Consider a farm composed of one square field divided into a grid of $(41 \times 41) = 1681$ ha. The agronomic characteristics of each grid cell are homogenous, but vary across cells. Crop yield (y) is a function f of three variables only: applied nitrogen fertilizer (x), soil nitrogen (c_1), and soil depth (c_2), which is unobservable. Soil nitrogen c_1 ranges between 3 and 82 kg/ha, while soil depth c_2 ranges between 1 and 82 cm. The spatial distribution of soil nitrogen, c_1, appears in Fig. 1.[1] To maintain simplicity, it is assumed that no unmanageable stochastic variables z affect yield. Eq. (2) presents the assumed form of the yield response function:

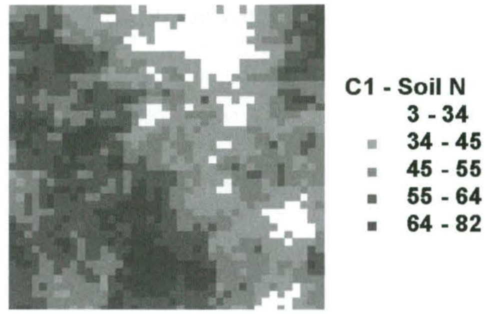

Fig. 1. Simulated spatial distribution of soil nitrogen, c_1.

$$f(x, c_1, c_2) = 2 + 0.6[x + c_1] - 0.0004[x + c_1]^2 + 0.004c_2 - 0.00001[c_2]^2 + 0.001[x + c_1]c_2. \quad (2)$$

Fig. 2 shows corn yield response to total nitrogen, $x + c_1$, given soil depth levels of $c_2 = 30$ and $c_2 = 50$. The figure illustrates how the functional form in Eq. (2) implies that deeper soil leads to a higher and steeper yield response to total nitrogen.

The 1681 ha in the field are indexed by (i, j), where $i, j = 1, \ldots, 41$, such that hectare (i, j) is the ith hectare to the east of the western border of the field, and the jth hectare to the north of the southern border. Calling $c_{1i,j}$ and $c_{2i,j}$ the values of soil-borne nitrogen and the unobservable characteristic on square (i, j), Eq. (2) implies (3):

$$\begin{aligned} f(x, c_{1i,j}, c_{2_{i,j}}) &\equiv f_{i,j}(x, c_{1i,j}) \\ &= \alpha_{i,j} + \beta_{i,j}[x + c_{1i,j}] + \gamma_{i,j}[x + c_{1i,j}]^2, \end{aligned} \quad (3)$$

[1] The spatial distributions of c_1 and c_2 were produced in TUBA (Zimmerman and Wilson, 1990), c_1 with an isotropic exponential semivariogram with a mean of 51 kg N/ha, a variance of 158 kg^2 N/ha^2 and a range of spatial correlation of 36 units, and c_2 with an isotropic exponential semivariogram with a mean of 45 cm, a variance of 140 cm^2, and a range of spatial correlation of 31 units. These distributions were chosen to reflect roughly the sort of spatial variation in characteristics evident in many Midwestern US farm fields.

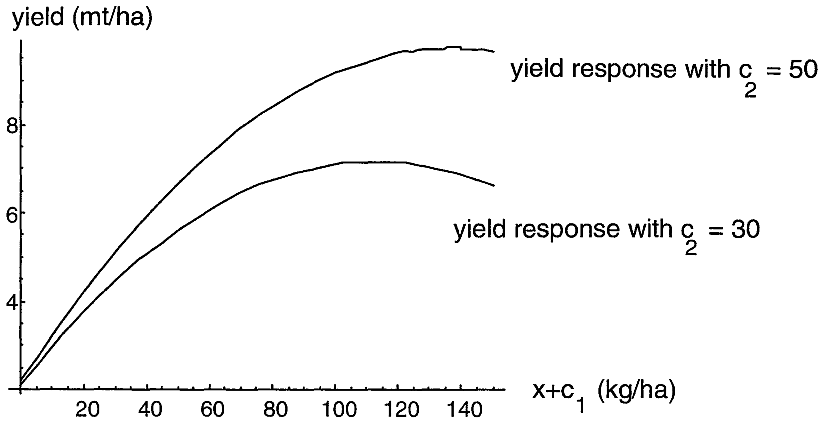

Fig. 2. Indicative yield response curves from the simulation.

where $\alpha_{i,j} = 2 + 0.004c_{2i,j} - 0.00001c^2_{2i,j}$, $\beta_{i,j} = 0.6 + 0.001c_{2i,j}$, and $\gamma_{i,j} = -0.0004$ for $i, j = 1, \dots, 41$. Eq. (3) shows that every one of the 1681 ha in the field has it's "own" yield response to total nitrogen, $f_{i,j}(x, c_{1i,j})$. The yield response of hectare (*i*, *j*) depends on the parameters $\alpha_{i,j}$, $\beta_{i,j}$, and $\gamma_{i,j}$. The producer is assumed to be able to sample the value of soil-borne nitrogen $c_{1i,j}$ in each hectare (*i*, *j*), but since variable c_2 is unobservable, it is not possible for the producer to estimate the yield response function in Eq. (2) directly. However, the producer can run (or hire a consultant to run) agronomic experiments that provide data with which to estimate the coefficients in Eq. (3) for every (*i*, *j*) for which an experiment is run.

Six scenarios illustrate how different levels of on-farm experimentation can be used to estimate the coefficients of the yield response functions in different parts of the field. For simplicity, it is initially assumed that this information can be obtained at no additional cost.

- Full information scenario: agronomic experiments are run on all 1681 squares shown in Fig. 3a, generating econometric estimates of all $\alpha_{i,j}$ and $\beta_{i,j}$ for $i, j = 1, \dots, 41$. These estimates are labeled $\alpha^{1681}_{i,j}$ and $\beta^{1681}_{i,j}$. For the purposes of the illustration, it is assumed that these estimates are perfectly accurate, so $\alpha^{1681}_{i,j} = \alpha_{i,j}$ and $\alpha^{1681}_{i,j} = \beta_{i,j}$, for $i, j = 1, \dots, 41$. (In reality, of course, econometric estimates of any cell's yield response function parameters would not be perfectly accurate because of the effects of unobserved variables and measurement error. In our simulations, we ignore econometric estimation error to focus on the economic effects of information.)
- Partial information scenarios: agronomic experiments are run only on a grid sample of the 1681 ha in the field. Sampling densities include 441, 121, 81, 36 and 25 ha, as shown in Fig. 3b–f, generating perfect knowledge of $\alpha_{i,j}$ and $\beta_{i,j}$ for the hectares on which experiments were run. This information is then spatially interpolated (kriged), to estimate the $\alpha_{i,j}$ and $\beta_{i,j}$ in each of the remaining squares. In the simulation, the kriged estimates, called $\alpha^k_{i,j}$ and $\beta^k_{i,j}$ ($i, j = 1, \dots, 41$; k is the sampling density) were based upon a fitted exponential semi-variogram using the Geostatistics for the Environmental Sciences software package (Gamma Design Software).

The information set for each sampling density k is denoted $\mathrm{IS}_k = \{\alpha^k_{1,1}, \beta^k_{1,1}, \gamma^k_{1,1}, \alpha^k_{1,2}, \beta^k_{1,2}\gamma^k_{1,2}, \dots, \alpha^k_{41,41}, \beta^k_{41,41}, \gamma^k_{41,41}\}$, with $k = 25, 36, 81, 121, 441, 1681$. With information set IS_k, the farmer derives an estimate of the individual yield response function for every hectare (*i*, *j*) in the field:

$$f^{k*}_{i,j}(x_{i,j}, c_{1_{i,j}}) = \alpha^k_{i,j} + \beta^k_{i,j}[x_{i,j} + c_{1_{i,j}}] + \gamma^k_{i,j}[x_{i,j} + c_{1_{i,j}}]^2. \quad (4)$$

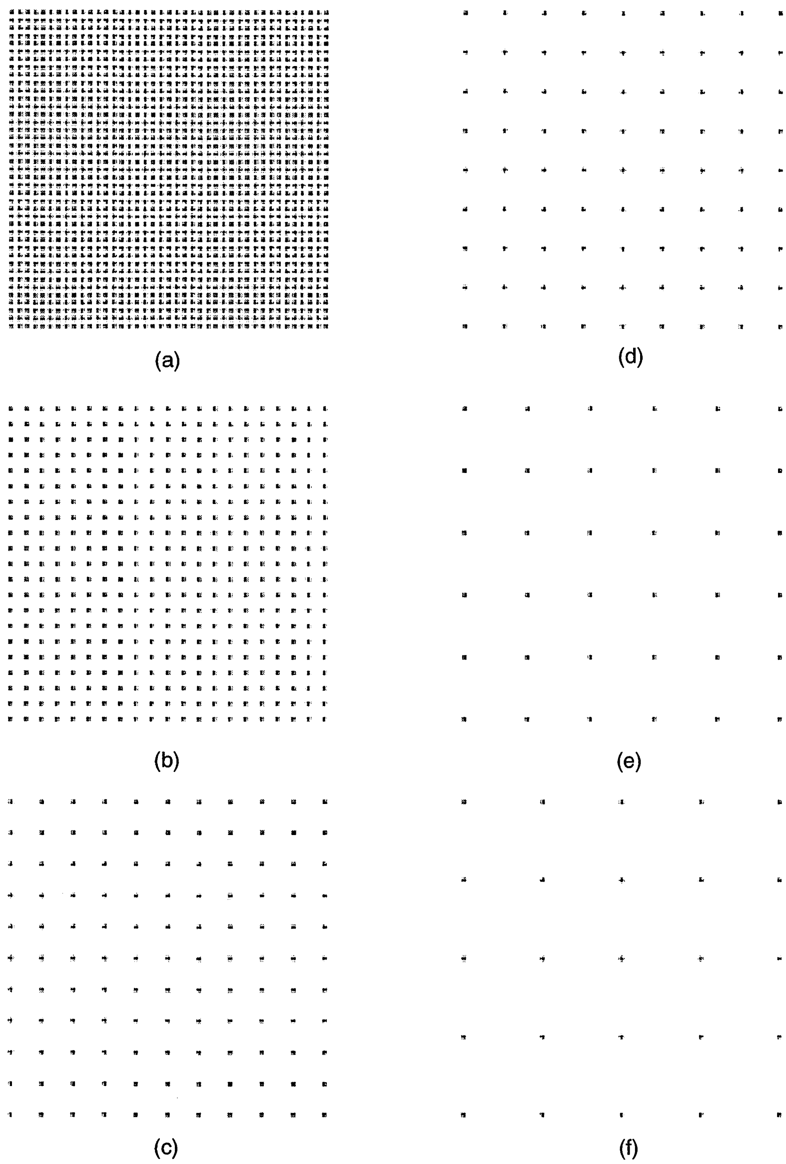

Fig. 3. Locations of the agronomic experiments at six densities. Panels (a) $k = 1641$, (b) $k = 441$, (c) $k = 121$, (d) $k = 81$, (e) $k = 36$ and (f) $k = 25$.

(Again note that for every cell (i, j), the farmer is assumed to know with certainty the amount of soil-borne nitrogen, $c_{1i,j}$, characterizing that cell.) For $k = 1681$ (full information), the estimate of each cell's production coefficients is perfect—the farmer knows the actual response function for each of the 1681 squares. As the number of experiments decreases, in general the accuracy of the coefficient estimates decreases, and the less information the farmer possesses about yield response.[2]

[2] Under URA, the gross margin over the applied nitrogen costs increases slightly when the number of cells in which an experiment is run goes from 36 to 81, from 81 to 121, from 121 to 441, and

The producer's profit maximization problem can be restated from Eq. (1), depending on his or her information set and the availability of either variable rate fertilizer application technology (VRA) or uniform rate application (URA). A farmer who has VRA is assumed to choose a nitrogen rate on every hectare so as to maximize net revenues:

$$\max_{(x_{1,1},\dots,x_{1,41}),\dots,(x_{41,1},\dots,x_{41,41})} \left[\sum_{i=1}^{41}\sum_{j=1}^{41} pf_{i,j}^{k*}(x_{i,j}, c_{1_{i,j}}) - wx_{i,j}\right] - g - v - F \tag{5}$$

A farmer who must use URA is assumed to choose a constant rate of application of x for the entire field so as to maximize net revenues:

$$\max_{x} \left[\sum_{i=1}^{41}\sum_{j=1}^{41} pf_{i,j}^{k*}(x, c_{1_{i,j}}) - wx\right] - g - F, \tag{6}$$

where p and w are the output price and the input price, assumed to be p = US\$ 98.33/Mg (i.e. US\$ 2.50/bu) and w = US\$ 0.33/kg (i.e. US\$ 0.15/lb), and for the moment g and v (information and VRA costs) are assumed to be 0, while other fixed costs (F) are irrelevant to the decision.

The solutions to the maximization problems in (5) are the economically optimal input application rates for the farmer using VRA with costless information set IS_k:

$$x_{i,j}^{k,\mathrm{VRA}*} = \frac{(w/p) - \beta_{i,j}^{k}}{2\gamma_{i,j}^{k}} - c_{1_{i,j}}, \quad \text{for } i, j, = 1, \dots, 41, \text{ and } k = 1681, 441, 121, 81, 36, 25. \tag{7}$$

The solutions to the maximization problems in (6) are the economically optimal input application rates for the farmer using URA with information set IS_k:

$$x_{i,j}^{k,\mathrm{URA}*} = \frac{(w/p) - (1/1681)\sum_{i=1}^{41}\sum_{j=1}^{41}\beta_{i,j}^{k}}{(2/1681)\sum_{i=1}^{41}\sum_{j=1}^{41}\gamma_{i,j}^{k}} - c_{1_{i,j}}, \quad \text{for } i, j, = 1, \dots, 41, \text{ and } k = 1681, 441, 121, 81, 36, 25. \tag{8}$$

Substituting (7) and (8) into the objective functions in (5) and (6) gives the producer's gross margins over applied nitrogen costs for all six information scenarios, for VRA and URA, respectively. The results are summarized in Fig. 4.

Two important results are evident in Fig. 4. First, given any amount of costless information available, the gross margin over the applied nitrogen costs are higher under VRA than under URA. The difference between these two shows the maximum amount that the farmer would be willing to pay to use VRA instead of URA. For every amount of information shown in Fig. 4 (i.e. to know with certainty the yield response functions for 25, 36, 81, 121, 441, and 1681 of the cells), the farmer is willing to pay a premium for VRA.

Second, the value of VRA versus URA increases with the amount of information that the farmer possesses. More information about site-specific yield response makes VRA worth more. Fig. 4 reports the result that given information set IS_{25}, the farmer would be willing to pay US\$ 1.60/ha for VRA. But

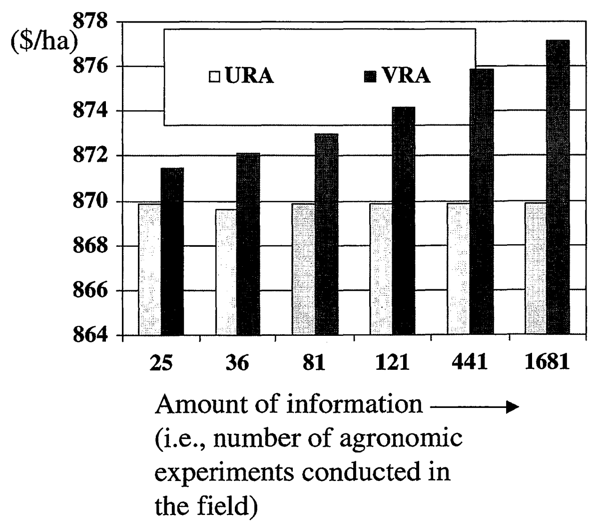

Fig. 4. Gross margins over applied nitrogen (x) costs.

from 441 to 1681. But it actually decreases slightly between 25 and 36 units of information. This latter result has been made possible by the way in which we have defined "quantity of information" in this heuristic example. As can bee seen in Figs. 3e and f, information not only about more cells, but about *different* cells are drawn from when 36 experiments are run instead of 25. Had we decided to get information from 36 cells by first using the information obtained from the original 25 and then adding information from 11 more cells, the result would have been that the gross margin over applied nitrogen costs would have increased slightly when the number of experiments run went from 25 to 36.

with more information, this willingness-to-pay for VRA increases, up to US$ 7.30/ha when the farmer possesses full information (i.e. has information set IS_{1681}). This implies that the marginal value of information is positive when the farmer possesses VRA. But in the example, the marginal value of information to the farmer using URA is basically zero—using URA, the farmer can make nearly as much money with IS_{25} as he can with complete information (IS_{1681}).[3] So, VRA makes information worth more. These results come about because variable rate technology and information are economic complements for the farmer. Having more information shifts demand (willingness-to-pay) for variable rate technology out, and having variable rate technology available shifts demand (willingness-to-pay) for information out.

The intuition behind these results is straightforward. Farmers who farm using URA have to choose one nitrogen application rate for their entire field. The optimal nitrogen application rate under URA will be too high for some parts of the field and too low for other parts, but on average, it will be profit-maximizing. Roughly speaking, the farming using URA wants to know the shape of the "average" of the yield response curves. To get reasonably good estimates of the coefficients of the "average" yield response curve does not take much information; a sample of the true yield response coefficients from 25 cells evenly-spaced throughout the field is large enough to give a very close estimate of the field's "average" yield response curve, which the farmer could know perfectly if he or she sampled the entire population of 1681 cells. Thus, agronomic experiments on just 25 of the 1681 ha of the field provided virtually all the information the URA farmer could use. But a farmer using VRA had use for more information, because he or she could use information about how the yield response curve coefficients in Eq. (3) are spatially distributed. The farmer using VRA wants to know more than the shape of the "average" response curve; he or she benefits from knowing the shapes of every response curve. Learning about the entire distribution of the 1681 response curves takes much more information than simply finding a good estimation of the mean response. Therefore, farming under VRA is much more information intensive than farming under URA.

6. Conclusions

Producers and agribusinesses remain fascinated with precision agriculture technology. Adoption, however, has lagged behind the expectations of many pundits. There are many good reasons for slow adoption of precision agriculture technology, not least of which is that researchers and farmers have initially focused excessively on in-field benefits from variable-rate fertilizer application derived when regional average fertilizer recommendations are used. This initial failure of focus is understandable; these regional average fertilizer recommendations have been used for decades with conventional application technology, and it was natural to use them initially to manage variable rate application. But our research suggests that because VRA technology has increased the value that can be added from site-specific data, new methods of developing application rate recommendations are needed.

The increased demand for site-specific information brought about by the appearance of precision technology calls for increased supply of site-specific information. Several researchers have begun trying to estimate site-specific response functions. Malzer et al. (1997) is an early published report of estimates of site-specific yield response functions. Bongiovanni and Lowenberg-DeBoer (2000b) obtained data from Argentine on-farm trials with combine yield monitors sensors, to develop corn nitrogen recommendations that incorporated slope position via spatial econometric techniques. Hurley et al. (2001) used a geostatistical approach to model omitted site variables and spatial error correlation in corn response to nitrogen. Swinton et al. (2002) developed topographic indices for wetness and insulation potential from Michigan on-farm trial data to estimate site-specific nitrogen response functions. But work in this area is only beginning.

Our research shows that the presence of VRA technology makes site-specific information worth more. This implies that two new forms of agronomic yield response research are now called for. First, more in-

[3] Based on the assumption of a single yield response function, Schnitkey et al. (1996) have shown that use of an economic decision rule to determine the URA input rate with site-specific sampling (e.g., of c_1) results in a different (more profitable) rate than one that is based upon whole-field average soil sampling.

formation about the meta-response function $f(x, c, z)$ needs to be gathered. This can be done through more long-term region-wide agronomic experimentation that systematically varies input levels to study their interaction with site-characteristics and stochastic variables over time.

The second type of research called for is that which will enable farmers to measure the site-specific characteristics c of their fields cheaply and accurately. For even if the meta-response function is known, farmers need to improve their estimates of $c_{i,j}$ for each site (i, j) if they are to possess the site-specific response functions $f(x, c_{i,j}, z)$ on their farms. Agricultural engineering research into finding inexpensive ways to develop maps of the site-specific characteristic levels $c_{i,j}$ on farms is currently well under way. Examples range from research into "on-the-fly" nitrogen stress sensors to research on the measurement of soil electroconductivity.

VRA technology may soon make it feasible for a farmer to use on-farm agronomic experimentation to bypass the challenge of estimating the meta-response function $f(x, c, z)$ and finding inexpensive ways to map the c variables. Through on-farm agronomic experimentation, it is possible to estimate a site-specific yield response function $f_{i,j}(x, z) \equiv f(x, c_{i,j}, z)$ without needing to know the meta-response function $f(x, c, z)$ or obtaining a map of the farm's site-specific characteristics $c_{i,j}$. It is a fascinating fact that while precision technology has increased the demand for site-specific information, it also has great potential to increase the *supply* of site-specific information. For precision technology can greatly reduce the cost of running agronomic experiments. Software for VRA equipment and yield monitors is now being developed to automate much of the running of agronomic experiments. Combining such on-farm experimental data with a time series of weather data will enable estimation of site-specific yield response functions $f_{i,j}(x, z) = f(x, c_{i,j}, z)$. Agricultural economists have a long history of estimating output response to input applications. Likewise, agricultural economists have developed an important body of research results on information value, based on managing variability—typically in temporal settings. With these tools, there exists major potential to develop further benefits from precision agriculture technologies, including the estimation of site-specific response relationships that permit truly spatially tailored input applications and create added value for site-specific information.

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