Staff Paper

FROM DATA TO INFORMATION: THE VALUE OF SAMPLING VS. SENSING SOIL DATA

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ABSTRACT

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PROBLEM STATEMENT

Site-specific agricultural information technologies are being tested by farmers across the United States. How and where site-specific farming (SSF) is adopted over the long term depends on the value of supplementary information it offers. Information has value when it leads to improved management decisions (Davis and Olson, 1985). In crop production, this may mean better crop yields, better crop quality, lower costs, or reduced agricultural pollution, all leading to more profitable, more sustainable farming.

For an information technology to be profitable to a business (and hence worth adopting without public intervention), the information value to the firm must outstrip its cost. Most current information to guide variable-rate application of agricultural inputs comes from manual soil sampling. Most commonly available as "grid sampling," such soil sampling is typically done on 2- to 3- acre grids on Midwestern farm fields. At prices of $5-10 per acre, it is viewed as expensive by many farmers who are otherwise interested in site-specific farming (Wehrspann, 1996; Swinton and Ahmad, 1996). Apart from cash costs, there is also an opportunity cost to the time delay between sampling and treatment.

Sensing technologies — both remote and in-field — represent an emergent alternative to soil sampling (Sudduth et al., 1997; Hummel and Birrell, 1997; Frazier

et al., 1997). They have the potential to offer a much lower marginal cost of data collection, better geographic accuracy, more intensive sampling and sometimes also the opportunity for immediate input application. However, sensing technologies tend to observe a proxy for the real crop input of interest. For example, crop nitrogen deficiency might be measured by infrared reflectance from leaves or from soil electrical conductivity, rather than a direct measure of soil nitrogen available for crop uptake. Apart from yield monitoring, agricultural sensing technologies have not yet seen widespread adoption by U.S. farmers.

This paper aims to develop a conceptual model of information economics related to site-specific crop management. That model is examined for indicators of:

1. How does the value of soil nutrient information vary between sampling and sensing technologies?
2. When could sensing be more profitable than sampling?
3. When could sensing yield less variable net returns than sampling?

REVIEW OF THE LITERATURE

Information value and how to measure it

Existing literature offers helpful context on how information is valued, how information is used in a spatially variable setting, and how much spatial information is required for optimal decision making.

Marschak (1968) defines information as a message which alters probabilistic perceptions of random events. This definition is used in statistical decision theory and has a great appeal among researchers of different disciplines (Chavas and Pope, 1984). Information in this sense acts as a means to decrease risk and has little or no value in the absence of risk. In general, risk characterizes those uncertain events whose outcomes alter the decision maker's welfare (Robison, 1987) as measured, for example, by the net income of farmers.

Given the link between information and risk, it is important to define how risk is measured. A practical working definition of risk can be based on mean and variance of the risky outcome variable under one of two broadly applicable conditions. The first is that the decision maker does not care about statistical moments of the probability distribution other than mean and variance. The second is that two or more risky outcome variables have probability distributions that are equal except for location (mean) and scale. This condition applies if "there exists some random variable X such that each [variable] Y_i is equal in distribution to $\mu_i + \sigma_i X$," where X is normalized to have mean 0 and variance 1 (Meyer, 1988). Under this definition, given two random variables Y_1 and Y_2 with the same mean, Y_2 is said to be riskier than Y_1 if Y_2 has a greater variance than Y_1 (Meyer, 1987; Pratt, 1964). This implies that probabilistic information is more valuable for managing Y_2 than Y_1.

Value of spatial information in agriculture

Having explored briefly how information is valued, we now turn to information use in a spatially variable agricultural setting. Feinerman, Bresler and Dagan (1989) studied the stochastic optimization of irrigation water in a spatially variable agricultural field. Their main objective was to predict mean yield based on available information and to determine which information level led to highest welfare for the decision maker. They found that spatial sampling ("conditional analysis") significantly improved yield prediction and efficiency of irrigation water use, as compared to assuming a uniform probability density function (pdf) for the whole field ("unconditional analysis").

Increased welfare under the conditional approach has also been found for temporal information embodied in pre-sidedress nitrate samples in corn (Babcock, Carriquiry and Stern, 1996). They used field plot data in estimating a corn production function, and showed that pre-sidedress nitrate sampling could reduce average fertilizer application rates between 15% and 41%.

Chavas and Pope (1984) showed that the value of costless information is always nonnegative. The more samples taken on a given field, the less uncertainty there is about the random variables and therefore the smaller the deviation between the nutrient that should "truly" be applied and what is applied based on measurements. However, sampling is not costless. Denser sampling costs more, and if the added value is less than the information cost, the decision maker's welfare will be lower. As Feinerman et. al. note, determining the optimal number of observations and the optimal spread over a field is a difficult statistical problem.

MODEL DEVELOPMENT AND DISCUSSION

Sampling versus sensing

As a prelude to the discussion that follows, we make a distinction between accuracy and precision. Accuracy in measuring a physical attribute or process describes how well the measurement reveals the true level of the attribute or process. Precision, on the other hand, refers to the resolution of the measurement instrument. Therefore a measure can have high precision but may be highly inaccurate if the measurement instrument is not well calibrated.

Many data collection tools are available for agricultural field management (Figure 1). Broadly speaking, data can be collected by sampling or sensing. Sampling refers to collecting individual observations from the population of interest, and using them to make inferences about the population as a whole. Importantly, sampling entails direct measurement of the attribute(s) of interest (e.g., nitrate nitrogen in a soil sample) for making management inferences. Whole-field soil sampling has been used for half a century to generate fertilizer recommendations at the field level. Site-specific approaches, such as sampling on a grid or by soil type within a field, use a denser sampling approach to make inferences about smaller areas within a field. Our

focus in this paper will be on grid soil sampling to represent all classes of in-field soil sampling.

Sensing refers to automated data collection using intensive sampling. Sensing frequently relies on a proxy variable that is correlated with the attribute of management interest. Remote sensing, for example, may entail measures of near-infrared reflectance from a cropped field as imaged from an airplane or satellite. Inferences for crop management must be based on extrapolating from the proxy

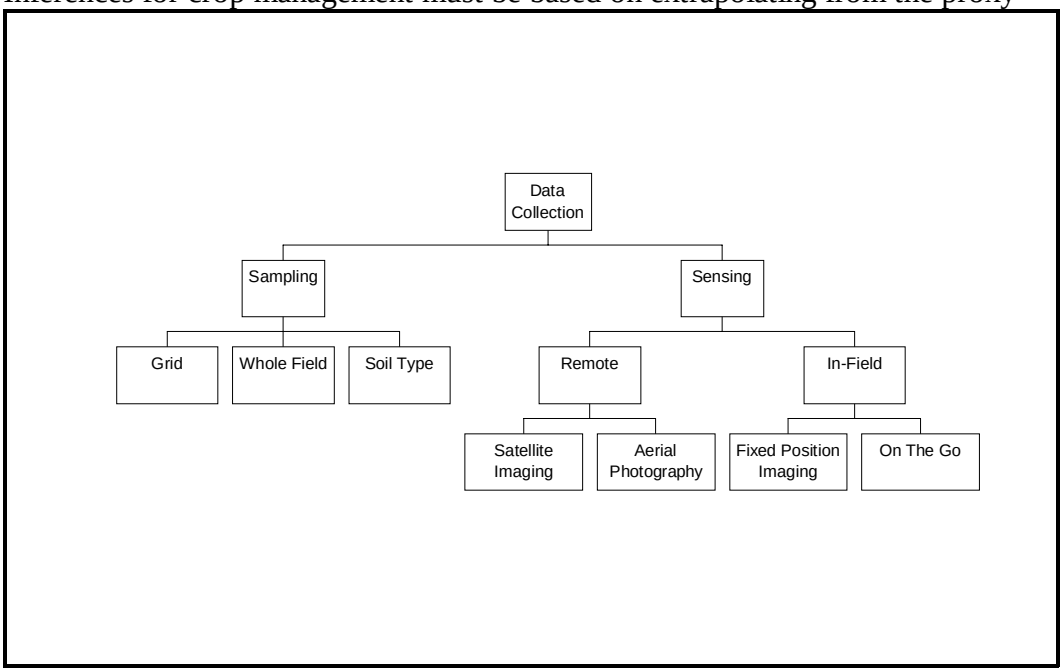

Figure 3: Typology of site-specific data collection media.

variable to predicted levels of the management variable of interest. This paper will focus on in-field soil sensing (IFSS), rather than remote sensing. A helpful illustration of IFFS is use of the soil electrical conductivity to predict the presence of soil nitrate N ions (NO_3^-). NO_3^- ions conduct electricity, but so can other soil media. Therefore electrical conductivity is an imperfect proxy for NO_3^- nitrogen. There is always a margin of error, however fine tuned or calibrated the measurement instrument. The automated data collection inherent in sensing yields a frequency of measurement that typically leads to high spatial accuracy. Because IFSS allows immediate variable rate technology (VRT) nutrient application, there is also potentially less time for nutrient status to change, a real problem with leachable NO_3^- nitrogen. Hence, IFSS may offer greater temporal accuracy as well as spatial accuracy to compensate for its potential proxy variable inaccuracy.

Conventional soil sampling has a higher level of measurement accuracy than IFSS (since the true attribute is being measured and not a proxy). However, grid sampling has relatively lower spatial and temporal accuracy since the measured values represent a larger area, and the elapsed time between measurement and application is relatively long. Ideally a farmer would like accurate location, accurate measurements and instantaneous application. What we have instead are “relatively

precise" location and "relatively imprecise" measurements for IFSS. If IFSS is linked to variable rate nitrogen fertilizer application on-the-go, then IFSS offers "relatively short" elapsed time before fertilizer application. For conventional sampling, we have "relatively imprecise" location, "relatively precise" measurements combined with "relatively long" elapsed time to application. This tradeoff between spatial and temporal accuracy and measurement accuracy is illustrated in Figure 2.

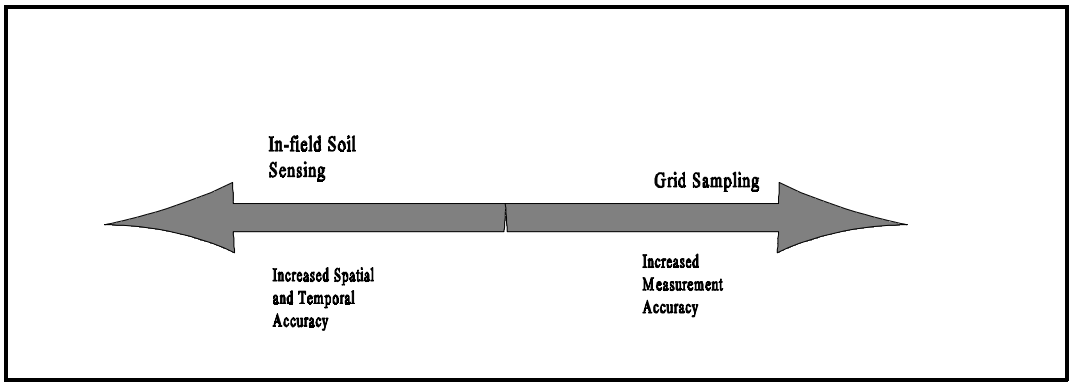

Figure 4: Spatial and measurement accuracy continuum.

Which sampling approach best suits farmer needs depends on a number of factors including cost of information acquisition, ease of use, and clarity of interpretation. The two key factors will likely be 1) expected profitability, and 2) variability of profits, especially if the farmer is risk-averse. In the remainder of this paper we seek to identify conditions under which sensing leads to higher expected net income or lower variance of net income than grid sampling.

A Model of Spatial Nitrogen Management

Consider the management of soil nitrogen in corn production. Nitrogen is a spatially and temporally random input to the corn production process. Following Babcock and Blackmer (1992) we assume that the mean yield y is a function only of the mean concentration of available soil nitrogen N_s at the time and location where the application decision is being made. Therefore the production relationship is represented by $f(N_s) = E(y|N_s)$. Binford et al. (1992) found that corn yield response to nitrogen is approximately linear up to a plateau level where nitrogen is no longer limiting. So the corn production function can be modeled by a linear response and plateau (LRP) function (Figure 3) as:

$$(3) \qquad y = \begin{cases} \alpha N_T + \epsilon^y & \text{if } N_T \leq N_r \\ Y_r + \epsilon^y & \text{if } N_T > N_r \end{cases}$$

where Y_r is maximum yield (at and above recommended nitrogen rate N_r), N_T is the total nitrogen in the soil after application, and N_r is the recommended level of nitrogen. ϵ^y is the yield disturbance, and is independent of any spatial, temporal and measurement disturbances in N measurement. We assume that the yield disturbance

is normally distributed such that $\epsilon^y \sim N(0,\sigma_y^2)$. $N_a = N_r - \hat{N}$ is nitrogen applied where $\hat{N}$ is a measure of the available nitrogen before application. We define $\hat{N}$ by equation (4), decomposing the associated sampling error into three components:

(4) $\hat{N} = N_s + \epsilon^t[\text{weather}(t^* - t^0)] + \epsilon^a(\text{area}) + \epsilon^p(\text{proxy})$

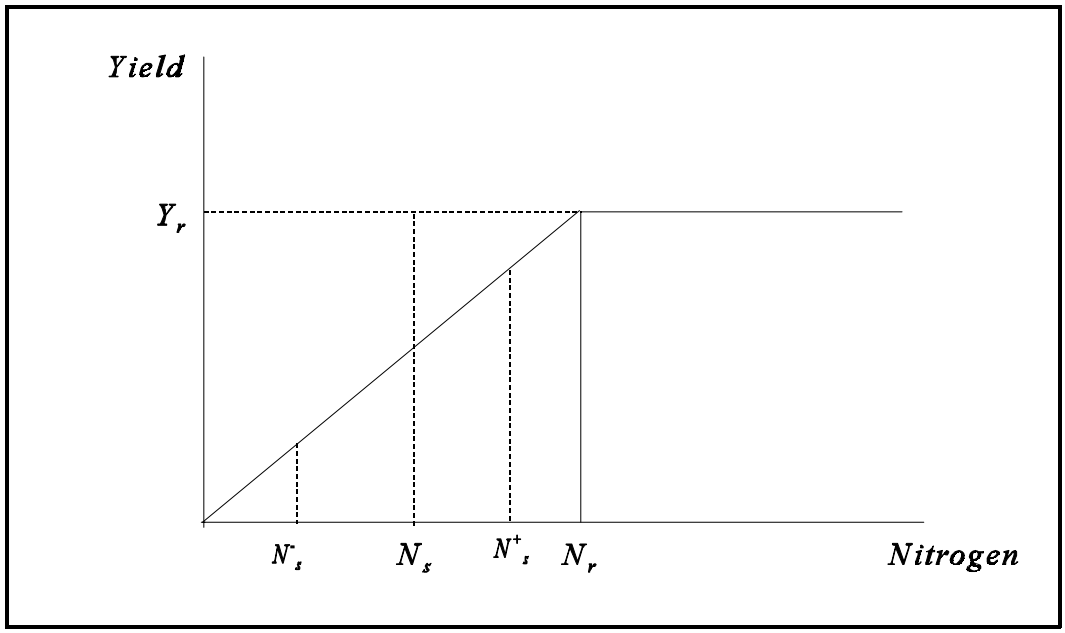

Figure 5: Hypothetical crop yield response to nitrogen.

where N_s is the "true" available nitrogen level in soil at time of testing; t^*, t^0 are respectively time of nutrient intake by plant and initial sampling time; ϵ^t is error due to passage of time between sampling and application; ϵ^a is spatial error, and ϵ^p is error due to measurement by proxy instead of the true attribute. We assume that all the disturbances are normally distributed according to: $\epsilon^t \sim N(0,\sigma_t^2)$, $\epsilon^a \sim N(0,\sigma_a^2)$, and $\epsilon^p \sim N(0,\sigma_p^2)$, implying that $E[\hat{N}] = N_s$.

With one variable input (nitrogen), profit is given as:

(5) $\pi = P(\alpha N_T + \epsilon^y) - w(N_r - \hat{N}) - \text{Fixed Cost}$

where P is product price and w is nitrogen fertilizer cost.

Mean profitability of sensing versus sampling

For mean profitability, we consider two scenarios for errors in measuring soil N. Under the first scenario, suppose the measured value of the available soil N is overestimated at N^+_s (Figure 3). Based on this measured value, the farmer under applies $N_r - N^+_s$ which falls short of recommended rate N_r by the amount $N^+_s - N_s$. Yield falls short of Y_r leading to a loss of potential profit.

Suppose instead the measured value of available soil N is underestimated at N^-_s. The farmer over applies $N_r - N^-_s$, with a surplus $N_s - N^-_s$. The over application does not increase yield above Y_r. However, there is waste of N fertilizer, leading to reduced profitability. Any deviation from the true N_s leads to a loss in profitability. The greater the deviation, the more drastic the loss in profits.

The error band $N^+_s - N^-_s$ shrinks as the number of sampling points increases over a given area (i.e, the denser the sampling procedure). By assumption, IFSS offers more spatial accuracy than grid sampling. Hence if we consider IFSS as denser sampling (i.e, we are still sampling but the area that each sample represents under IFSS is much smaller), we can conclude intuitively that IFSS has a smaller error band leading to smaller overestimates and underestimates of available nitrogen and therefore smaller expected loss in profitability relative to conventional grid sampling.

Mathematically, we observe the same result. We first assume that a rational farmer will apply soil N as long as the marginal value product (MVP = *P*df(N)/dN*) is greater than the cost of the input (w). In our LRP corn production model, this implies that $P\alpha > w$ up to point N_r. If the error band, $N^+_s - N^-_s$, is narrower for sensing, then $N^+_{sen} < N^+_{sam}$. Now consider the overestimate scenario described above. We introduce two new symbols: N^+_{sam} (overestimated measure of N_s under sampling) and N^+_{sen} (overestimated measure of N_s under IFSS). We also define $\pi_j = PY_j - w(N_r - N^+_j)$ (j = sen, sam). Then the difference in expected profitability between sensing and sampling depends on whether the value of increased yield from sensing is greater than the increased cost of fertilizer, $\pi_{sen} - \pi_{sam} = P(Y_{sen} - Y_{sam}) + w(N^+_{sen} - N^+_{sam})$. From our assumptions, $P(Y_{sen} - Y_{sam}) = P\alpha\,(N^+_{sam} - N^+_{sen}) > w\,(N^+_{sam} - N^+_{sen})$. So IFSS leads to a higher expected profitability given overestimation of N_s.

Scenario two is more straightforward. Underestimation of soil N leads to over application of N. However over application leads to yield of $Y_{sam} = Y_{sen} = Y_r$. We observe that the wasted fertilizer, $N_r - N^-_s$, is smaller for IFSS then for sampling. Therefore $\pi = PY - w(N_r - N^-_s)$ is higher under IFSS.

Variance of profitability in sensing versus sampling

The analysis of risk effects from soil sensing versus sampling depends upon the probability distributions of the input of interest – nitrogen in this case. In the mean-variance framework developed above, risk effects hinge on variances and covariances. Building on the profit expressing in Equation (5), we assume that the time-lag variability of soil nitrogen, N_s, is unrelated to either spatial accuracy or proxy measurement variability($cov(\epsilon^t,\epsilon^a) = cov(\epsilon^p,\epsilon^t) = 0$), but that the proxy measurement variability increases with spatial variability ($cov(\epsilon^p,\epsilon^a) > 0$). These generic assumptions hold for both conventional sampling and IFSS.

The three components of soil attribute assessment risk are assumed to vary systematically between grid sampling and soil sensing. For grid sampling, we assume there exists no proxy error ($\sigma_p^2 = 0$) because soil analysis laboratories directly measure NO_3^- nitrogen. We also assume that $\sigma_a^2>0$ and $\sigma_t^2>0$, and that both variances are large. The assumption concerning spatial variability is reasonable considering that a

particular sample represents a grid cell area typically 2.5 acres. Such an area may contain great agronomic variability (Pierce and Mueller, 1997). The assumed variability due to time lags is based on how water-soluble soil nitrate levels fluctuate in response to precipitation during the weeks that typically elapse between soil sampling and pre-sidedress nitrogen application.

Given these assumptions, the variance of $\hat{N}$ with grid soil sampling is:

$$(6) \qquad \sigma^2_{\hat{N}}(sam) = var(N_s + \epsilon^t + \epsilon^a + \epsilon^p) = \sigma^2_t + \sigma^2_a.$$

In general with the LRP corn production function, the variance of profit is:

$$(7) \qquad \sigma^2_\pi = \begin{cases} var(\alpha P N_T + P\epsilon^y - wN_r + w\hat{N}) & if\ N_T < N_r \\ var(PY_r + P\epsilon^y - wN_r + w\hat{N}) & if\ N_T \geq N_r \end{cases}$$

Inserting the variance of $\hat{N}$ with grid soil sampling yields the variance of profit under soil sampling:

$$(8) \qquad \sigma^2_\pi(sam) = \begin{cases} P^2\sigma^2_y + \sum_{j=a,t} [(w-\alpha P)^2\sigma^2_j + 2P(w-\alpha P)cov(\epsilon^y,\epsilon^j)] & if\ N_T < N_r \\ P^2\sigma^2_y + \sum_{j=a,t} [w^2\sigma^2_j + 2Pwcov(\epsilon^y,\epsilon^j)] & if\ N_T \geq N_r \end{cases}$$

The risk effects of in-field soil sensing arise from the distinct nature of sampling disturbances associated with sensing. To begin, assume that input application on-the-go in response to the sensory input makes temporal disturbance negligible, so $\sigma_t^2 = 0$. Likewise, since sensing involves very dense sampling, we assume that although locational disturbance is nonzero ($\sigma_a^2 > 0$), it is small. Finally, we assume that there is measurement error due to use of a proxy for the true attribute of interest ($\sigma_p^2 > 0$), but that there is medium to high correlation between the proxy measurement and the true level of nitrogen.

The variance of $\hat{N}$ with sensing is thus given as:

$$(9) \qquad \sigma^2_{\hat{N}}(sen) = var(N_s + \epsilon^t + \epsilon^a + \epsilon^p) = \sigma^2_p + \sigma^2_a + 2cov(\epsilon^p,\epsilon^a)$$

Inserting this expression into equation (7) yields the variance of profit with in-field soil sensing:

$$(10) \quad \sigma^2_\pi(sen) = \begin{cases} P^2\sigma^2_y + 2(w-\alpha P)^2 cov(\epsilon^p,\epsilon^a) + \sum_{j=a,p} [(w-\alpha P)^2\sigma^2_j + 2(w-\alpha P)Pcov(\epsilon^y,\epsilon^j)] \\ \qquad if\ N_T < N_r \\ P^2\sigma^2_y + 2w^2 cov(\epsilon^p,\epsilon^a) + \sum_{j=a,p} [w^2\sigma^2_j + 2wPcov(\epsilon^y,\epsilon^j)] \\ \qquad if\ N_T \geq N_r \end{cases}$$

Variability of profits under the two scenarios

Locational error is likely to be higher under grid sampling than under sensing [$\sigma_a^2(\text{sam}) > \sigma_a^2(\text{sen})$], as assumed above. The general form for the difference in profit variability under the two scenarios is therefore:

$$\sigma_\pi^2(sam) - \sigma_\pi^2(sen) =$$

$$(11)\begin{cases}(w-\alpha P)^2[\sigma_{\hat{N}}^2(sam)-\sigma_{\hat{N}}^2(sen)]+2P(w-\alpha P)[cov_{sam}(\epsilon^y,\hat{N})-cov_{sen}(\epsilon^y,\hat{N})] & if\ N_T<N_r \\ w^2[\sigma_{\hat{N}}^2(sam)-\sigma_{\hat{N}}^2(sen)]+2Pw[cov_{sam}(\epsilon^y,\hat{N})-cov_{sen}(\epsilon^y,\hat{N})] & if\ N_T \geq N_r\end{cases}$$

Given (11), we have equal variability of net income for sampling and sensing in two instances. The first is if $P\alpha = w$ when total nitrogen (N_T) is less than the recommended rate (N_r) or if $w = 0$ when total nitrogen exceeds N_r. These conditions imply that the value of the yield gain just equals the cost of N, so any N rate would be equally profitable. The second instance is if the variances of the sampled nitrogen levels are equal for sampling and sensing, [$\sigma_N^2(\text{sam}) = \sigma_N^2(\text{sen})$]. However, grid sampling will lead to riskier profit if it has higher variance in sampled soil nitrogen level and if that soil nitrogen level covaries with crop yield:

$$(12)\qquad \begin{aligned}&\sigma_\pi^2(sam) > \sigma_\pi^2(sen)\ \ if\\ &\{\sigma_{\hat{N}}^2(sam) > \sigma_{\hat{N}}^2(sen)\}\ \ and\ \ \{cov_{sam}(\epsilon^y,\hat{N}) \geq cov_{sen}(\epsilon^y,\hat{N})\}\end{aligned}$$

This general form however does not reveal much. We therefore use the profit variability expressions in (8) and (10) and add the simplifying assumption that yield variability (ϵ^y) is independent of spatial, temporal and measurement disturbances, to obtain:

$$\sigma_\pi^2(sam) - \sigma_\pi^2(sen) =$$

$$(13)\ \begin{cases}(w-\alpha P)^2[(\sigma_{a(sam)}^2-\sigma_{a(sen)}^2)+(\sigma_{t(sam)}^2-\sigma_{p(sen)}^2)]-2(w-\alpha P)^2 cov(\epsilon^p,\epsilon^a) & if\ N_T<N_r \\ w^2[(\sigma_{a(sam)}^2-\sigma_{a(sen)}^2)+(\sigma_{t(sam)}^2-\sigma_{p(sen)}^2)]-2w^2 cov(\epsilon^p,\epsilon^a) & if\ N_T \geq N_r\end{cases}$$

By assumption, the covariance between the proxy error and spatial error is positive. However, we cannot unambiguously determine the sign of the difference between temporal variability in N_s and proxy measurement variability. We can say that if temporal variability is sufficiently high and spatial variability sufficiently low relative to proxy measurement variability, then profit variability under sampling is higher than profit variability under sensing. This amounts to a trade-off between the proxy measurement variability of sensing, on the one hand, and the spatial and temporal soil variability of grid sampling, on the other. If total variability is higher under grid sampling than under in-field soil sensing, then sensing information has greater value to a risk-averse decision maker.

CONCLUSIONS

This paper has used a conceptual model to show that both expected profit and variance of profit from site-specific input management depend on the accuracy of spatial information. The relative merits of sensing information are that it tends to be more accurate spatially and temporally (if used for VRT input control) than soil sampling information. On the other hand, soil sampling tends to give more accurate measurements. Which of the two is preferable depends upon the relative importance of location, timing, and measurement error.

This result has important implications for profitable site-specific input management today, as well as for the development of new site-specific technologies in future. Regarding profitable management, the payoffs to sensing are highest 1) when sensor equipment gives a fairly accurate measure of desired attributes, 2) when timeliness matters (e.g., plant growth hormone or nitrogen fertilizer application), 3) when in-field micro-variability is great. By contrast, the payoffs to in-field soil sampling methods (by grid, soil type, or other) are highest when 1) sensor equipment is not reliable, 2) timeliness does not matter (e.g., phosphorus or potassium fertilizer application), and 3) spatial variability occurs on a larger scale. Grid sampling tends to impose only a variable cost for data collection labor and laboratory analysis. On the other hand, in-field sensor equipment is a capital good with a high fixed cost for equipment and operator learning, so its cost per acre declines with the land area over which it is used.

From the standpoint of technological innovation, the spatial and temporal accuracy advantages of sensing combined with far lower cost-per-measurement suggest continuing intensive research and development of better sensor technologies, both in-field and remote. The focus will be on reliable equipment that minimizes proxy measurement error. In the meantime, there remains large scope for empirical measurement of the relative profitability and riskiness of sensing versus sampling technologies in the market.

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