

Soil Sampling, Especially for N and P: Does it Pay?

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Abstract

How often should I spend the time and money to soil sample? How many samples should I collect in a field? How is the profit from soil sampling affected by crop and fertilizer prices? Do higher grain prices coupled with higher fertilizer prices mean more, or less, fertilizer should be applied? In terms of cash rent or land value, how much more is land worth that has higher soil fertility? Is grid soil sampling worth its cost? Or, can electronic sensors do an adequate job for less money? By touching on a broad array of soil sampling issues, this session will begin to answer questions like those noted here.

Soil Sampling, Especially for N and P: Does it Pay?

Background

Most crop producers in the U.S. have been making fertilizer decisions for decades. Typically, managers make decisions regarding product and application rates based on information from many sources, for example, personal experience, other producers, crop consultants, and fertilizer dealers. Also, for decades crop consulting firms, soil testing laboratories, and universities have provided fertilizer recommendations based explicitly on soil tests. But, although managers routinely acknowledge the potential benefits to soil testing, far fewer actually use it. For example, a Kansas State University report (Bernardo, et al., 2001) showed that about 35% of Kansas corn producers soil sample and only 14% of Kansas milo producers. Also, a quick web search revealed a number of other reports showing that percent of producers who soil sample typically is under 30%. This suggests that the expected gains to using soil testing for many producers are insufficient to cover expected costs associated with soil testing. But, this situation is similar to other farm management aspects in that “If the profits were that obvious, we’d all be soil sampling.”

Accurately predicting yield response to fertilizer is notoriously difficult. Intrinsically, continual biological change within soils ensures substantial buffering capacity and causes effects of added fertilizer to be smoothed across years. Large weather events such as droughts, excess precipitation, or hail, exacerbate the problem of “seeing a fertilizer response” in any particular year. Additionally, different management practices across farmers further mask yield response to fertilizer. Thus, it is not unusual to hear farmers say “I put 40 lb/acre of nitrogen (N) fertilizer on my wheat this year and my neighbor put on 60 and I couldn’t see a difference.” With phosphorus, natural buffering is even more pronounced. Thus, a farmer who applies 40 lb/acre of phosphate (P_2O_5) may see no difference relative to his neighbors who do not even use phosphate fertilizer, especially for any particular year.

Given soil’s natural buffering, and considering the intrinsic inaccuracies of laboratory tests of soils, it should not be surprising that farmers are reluctant to more accurately determine appropriate fertilizer rates with soil testing. Yet, it should be remembered that selecting optimal (profit-maximizing) fertilizer rates is an on-average phenomenon, and should be assessed over years rather than by a single year’s results. In that setting, small average annual increases in yields or reductions in average annual fertilizer rates often can justify the cost of soil testing. And, as with most farm management decisions in a highly competitive environment, the devil is in the details. That is, typically only small changes in average annual revenues or costs separate the successful and surviving farms from the unsuccessful and disappearing ones.

An N recommendation formula

University and commercial soil testing laboratories, as well as some crop consulting firms, routinely provide (often online) mathematical formulas depicting recommended fertilizer rates for crops. Typically, but not always, recommended rates depend on soil tests. For example, Eq. [1] shows the nitrogen (N) fertilizer recommendation for corn based on Kansas State University’s (KSU) recently-revised (2003) fertilizer recommendations (MF-2586).

$$[1] \quad \text{Corn } Nrec = (1.6 * YG) - (20 * OM) - \text{Profile } N - \text{Manure} \\ - \text{Other } N \text{ Adjustments} - \text{Previous Crop Adjustments} .$$

In Eq. [1], *Corn Nrec* is N fertilizer (*fertN*) in lb N/acre, *YG* is yield goal in bu/acre, *OM* is percent soil organic matter in the top 6 inches of soil, *Profile N* is lb of nitrate nitrogen (NO₃-N) per acre in a 2-foot soil profile, often referred to more simply as lb N/acre, and the other categories are to remind the user that other N credits may need to be considered. Guidelines for the other credits are suggested in MF-2586. *Nrec* formulas routinely depend on yield goal (*YG*). Though rarely made explicit, *YG* is typically taken to be 110% of statistically expected (i.e., historical, or possibly trend-adjusted average) yield. Also, a 30 lb N/acre minimum and a 230 lb N/acre maximum (300 for irrigated corn) underlies Eq. [1].

The *OM* term in Eq. [1] represents the expected mineralization of organic matter to usable N fertility during the production cycle. Thus, a soil with 2.0% *OM* is expected to need 20 lb/acre less *fertN* than a soil with only 1.0% *OM*. Although not shown, KSU's wheat *Nrec* gives a credit of only 10 lb N/acre for each percent *OM*, since wheat production occurs during cooler temperatures than corn, implying less N mineralization.

Soil sampling depth

Most of the soil test information used in KSU's fertilizer recommendation formulas assumes a 0-6 inch soil sampling depth. A notable exception is *Profile N*, as described above (other mobile nutrients such as sulfate and chloride also use the deep test). Historically, under traditional tillage practices, it likely did not matter that much whether a soil sample was 0-4 inches or 0-8 inches, since the soil at these depths generally was thoroughly mixed by tillage. With reduced tillage, and especially no-till, soil sampling depth probably is more critical. For example, percent organic matter likely will be much higher in the top few inches than in the 4-8 inch depth. Thus, a sampler who samples to 8 inches rather than the recommended 6 inches, likely will over-apply *fertN* using KSU's *Nrecs*, since the average percent organic matter in 8 inches of soil is less than in 6 inches, resulting in less assigned credits in Eq. [1]. This situation also would apply especially to soil pH, where no-till must rely on rainfall to integrate a lime application to increasing soil depths.

Recognizing that crop roots routinely go much deeper than 8 inches for water and N, soil testing labs in the Great Plains routinely base *Nrec*'s on profile N tests of 0-24 inches or 0-36 inches. KSU assumes 0-24 inches. Having said that, it is likely that deep soil sampling for N is rare. Many samplers just request "running an N test" on the same shallow soil samples used for other tests such as phosphorus (P) or soil pH. In recognition of that, soil testing laboratories generally assign default values to the un-sampled portion of the soil profile when making *Nrec*'s. But, it should be noted that such default values generally are quite conservative, in order to minimize the risk of under-application of *fertN*. For example, when only a shallow (0-6 in.) test has been pulled, KSU assumes 3 ppm for the 6-24 in. portion to comprise the *Profile N* value plugged into Eq. [1].

Most labs measure soil nutrients on the basis of a concentration portion (e.g., ppm), thus requiring that such measures be recast in units more familiar to users (e.g., lb/acre). Generally, it is assumed

that a 1-inch depth of soil over an acre weighs around 0.3 million lb. Hence, a 1 ppm concentration in a 6-inch depth of soil would imply 1.8 lb/acre (i.e., $1 \times 0.3 \times 6$). Sometimes this value is rounded to 2 to generate the rule of thumb “take ppm times 2 to get lb/acre.” Actually, assuming the soil weight of 0.3 million lb/acre-inch, this rule of thumb would be more appropriate for a 0-7 inch sampling depth. The 3 ppm default used by KSU in its *Nrec* would imply 16.2 lb N/acre in the 6-24 inch soil slice (i.e., $3 \times 18 \times 0.3$), which would be added to the lb/acre calculated from the 0-6 inch sample actually tested. Yet, when actually sampled and by KSU’s records, such deep samples often reveal values much higher than those implied by the default deep ppm, which is especially true for western Kansas. For example, 8 years of soil testing on the Kastens farm in Rawlins County Kansas (in NW Kansas) revealed 6-24 inch samples that averaged 6.3 ppm, which is more than twice the default value.

P recommendations

Eq. [2] shows the sufficiency phosphate (P_2O_5) fertilizer recommendation for corn based on KSU’s MF-2586 publication.

$$[2] \quad \text{Corn Prec} = 50 + (0.2 * YG) - (2.5 * STP) - (0.01 * YG * STP) .$$

In Eq. [2], *Corn Prec* is P fertilizer (*fertP*) in lb P_2O_5 /acre, *YG* is yield goal in bu/acre, *OM* is percent soil organic matter in the top 6 inches of soil, *STP* is the Bray 1P soil test value (0-6 inches) for P in ppm. Underlying Eq. [2] is an assumption that the minimum *Prec* is 15 lb/acre whenever *STP* < 20.

Different soil testing labs use different *STP* tests for different soils and so care should be taken to use fertilizer recommendations that have been designed specifically for the test involved. KSU’s *Prec*’s are specified in terms of the Bray 1P extractable P test. Another popular test for P is the Mehlich III extractable P test. KSU considers it to be similar enough to the Bray 1P test that the two can be exchanged for each other. A third test (typically used in high pH soils) is the Olsen P test. When working with this test, KSU suggests that its value first be multiplied by 1.6 before insertion in Eq. [2]. Other P tests and more complex conversion formulas are provided by Diaz-Zorita and Buschiazzo (2004). For example, that publication suggests the following conversion formula: Bray 1P = $9.7 + 0.99 * \text{Olsen P}$.

It is worth noting that *Prec*’s are for phosphate fertilizer, which is P_2O_5 , not for elemental P. If elemental P information is required, it can be obtained by multiplying a phosphate quantity by 0.43, which is the atomic-weight portion of P in P_2O_5 . Also, though a P is used in the standard N-P-K fertilizer notation, it really means phosphate or P_2O_5 . Thus, the 10-34-0 liquid fertilizer P formulation contains 34% P_2O_5 .

In the *Nrec* and *Prec* formulas provided above it is fundamental that higher soil test levels lead to lower fertilizer recommendations. That is, it must be the case that fertilizer and soil fertility are economic substitutes for each other in crop production. Higher levels of *either* fertilizer or fertility lead to higher crop yields. Generally, the management question around fertilizer is, Given the soil test, how much fertilizer should I apply to maximize my profit? That is, what rate should I

apply, so that the last increment of fertilizer induces just enough yield increase to offset its cost? For example, Figure 1 shows how *STN* impacts KSU's *Nrec*'s in corn and wheat production at an *OM* level of 1.6, and expected yields (*EY*) of 75 bu/acre for corn and 45 bu/acre for wheat (corresponding yield goals are 10% higher than expected yields). That the two *Nrec* lines in the figure are nearly on top of each other is somewhat coincidental, but not totally. That is, the corn yield (75) and wheat yield (45) are considered to be reasonable expected yields in NW Kansas for a wheat-corn-fallow (WCF) crop rotation. That KSU assumes a minimum *fertN* value of 30 lb/acre in its *Nrec*'s is immediately apparent.

Figure 2 shows how KSU's *Prec*'s are impacted by *STP* levels. Again, the corn and wheat lines are essentially identical. KSU assumes a minimum *Prec* of 15 lb/acre whenever *STP* is less than 20 ppm and a 0 *Prec* above 20 ppm. This should show up as a vertical line in the figure at *STP* = 20. But, since 20 ppm was not modeled in the figure, a straight line connects the two modeled points of *STP* = 19 and 21.

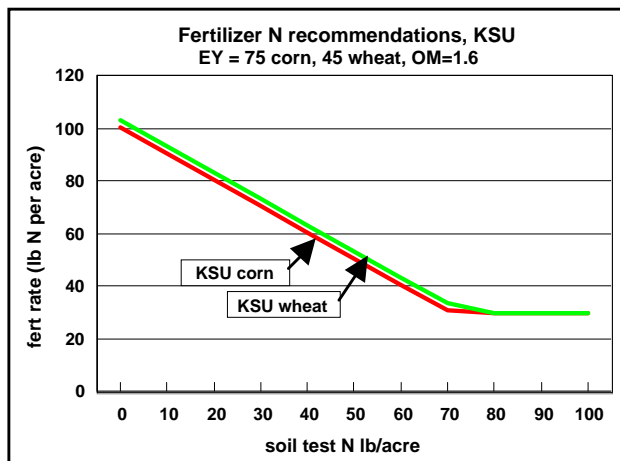


Figure 1

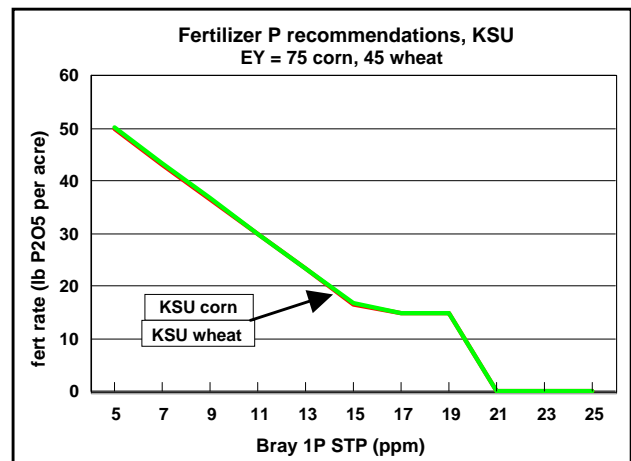


Figure 2

Using fertilizer to change soil fertility

If it happens that fertilizer can impact not only crop yields but also soil fertility, the fertilizer decision becomes more complex than that shown in Figures 1 and 2. That is, depending on the relative yield response to fertilizer and fertility, it may pay to place “extra” fertilizer today to build up soil fertility for future crops, especially if the soil nutrient in question is fairly immobile. In such settings, the focus routinely turns to implementing a fertilizer program that targets a critical soil test level rather than one that merely responds to existing levels of fertility. The idea of impacting soil fertility with input applications has long been well known for the lime/soil pH decision, where lime is placed today to impact soil pH for years to come. In this extreme case, lime applications are not viewed as directly impacting crop yield, but rather as impacting soil pH which does impact yield. Hence, a critical level of soil pH, say 6.5, is targeted by a liming program.

Because P is mostly immobile in the soil, it is a candidate for considering how *fertP* might impact *STP*. Consequently, KSU has followed suit with other states in providing a P build-maintenance

Prec. The underlying framework targets a critical *STP* level (20 ppm for KSU), above where no economic response to annual applications of *fertP* are expected. But, since harvested crops remove P from the system, *fertP* rates equal to crop removal rates are required to prevent *STP* from falling below the critical level of 20 ppm. Hence, upon reaching the critical *STP*, it must be maintained with crop removal *fertP* rates. KSU assumes that it takes 18 lb/acre of P₂O₅ above crop removal to increase *STP* by 1 ppm. Hence, to induce a “jump” from an *STP* level of say 12 ppm to the critical level of 20 ppm would take an application rate of 144 lb P₂O₅/acre above crop removal rates (i.e., 18*[20-12]). KSU assumes crop P removal rates to be 0.33, 0.40, 0.50, and 0.80 lb P₂O₅ per bushel harvested, for corn, milo, wheat, and soybeans, respectively. Hence, assuming an expected 40 bu/acre wheat crop (20 lb P₂O₅ removal), 164 lb P₂O₅/acre would be recommended to make the jump from 12 ppm *STP* to 20. This *Prec* is formalized in the following equation:

$$[3] \quad Prec = \frac{18 * (20 - STP)}{\text{years to build}} + P_2O_5 \text{ removal in crop} .$$

Though Eq. [3] depicts how *fertP* might change *STP*, it is critical to note that, unlike Eq. [1] and [2], it does not explicitly provide a recommendation that maximizes profit. In particular, though MF-2586 contains tables showing build-maintain *Prec*'s by *STP* for “years to build” numbers of 4, 6, and 8, it offers no guidelines regarding how many years a farm manager should actually take to build up *STP*. Certainly, unless a land tenant will get compensation for the extra *fertP* expense, there would be little reason for him to continue to build *STP* in the later years of a rental contract. Nonetheless, insofar as KSU's new build-maintain *Prec*'s will spurn such relevant questions, they might pave the way for a more comprehensive recommendation down the road that explicitly takes into account such features as length of land tenancy.

Yield response models

Given that a farm manager chooses to soil test, fertilizer recommendation formulas like Eq. [1] and Eq. [2] provide some insight into what KSU believes are optimal (profit-maximizing) fertilizer rates. Even in the absence of soil testing, assuming one is willing to plug in typical or average soil tests, useful fertilizer recommendations should emerge. On the other hand, such formulas provide absolutely no insight to help answer potentially relevant questions such as the following ones. Does it generally pay to soil sample at all? Or, would I be better off applying what my neighbor does or what I typically have done in the past? Assuming that soil sampling might be worthwhile at least once in awhile, how frequent should I do it? How many samples should I collect in a field? How are the returns to fertilizer and to soil sampling affected by crop and fertilizer prices? Do higher grain prices coupled with higher fertilizer prices mean more, or less, fertilizer should be applied? In terms of cash rent or land value, how much more is land worth that has higher soil fertility? Is grid soil sampling worth it's cost? Or, can electronic sensors do an adequate job for less money?

Answering questions like those posed in the preceding paragraph requires yield models that depict expected crop yields as mathematical functions of levels of managed or measured variables such as fertilizer rates and soil fertility levels. Only with such models can we determine how much

profit might be conceded by applying the “wrong” fertilizer rates. Only then can we learn just how fast we should build up *STP* to maximize profits.

Though fertilizer recommendation formulas do not depict yield response to crop inputs, Kastens, Schmidt, and Dhuyvetter (KSD) have devised a way to uncover expected yield models that likely underlie such fertilizer recommendations (process described in the referenced publication). That is, given long-run historical crop and fertilizer prices, using KSD yield models to simulate crop yields from input variables will result in profit-maximizing fertilizer recommendations that are similar to those provided directly by *Nrec* and *Prec* formulas such as those in Eq. [1] and [2]. The basic KSD yield model formulation is

$$[4] \quad Yield = YG * (1 - B1 * \exp\{-B2 * fertP - B3 * STP\}) * (1 - B4 * \exp\{-B5 * fertN - B6 * STN - B7 * OM\}) ,$$

where, the B1-B7 expressions represent numerical constants, exp denotes the exponential function, and all other expressions already have been discussed. For our purposes here, a separate model like Eq. [4] was estimated for each of corn and wheat. The associated numerical constants are provided in Table 1. The numerical values in Table 1 can be combined with the mathematical structure of Eq. [4] in a simple spreadsheet to analyze the expected impact of numerous management decisions.

Table 1. Parameter estimates of yield models

parameter	corn model value	wheat model value
B1	0.8993	0.7875
B2	0.0734	0.0635
B3	0.1453	0.1309
B4	0.9808	0.7939
B5	0.0219	0.0234
B6	0.0170	0.0171
B7	0.3989	0.1121

To estimate the models described we simulated 10,000 observations that can be considered farm production fields across space or time. Each field was assigned a random value for *STP*, *STN*, *OM*, and crop yield (thus also *YG*). We assumed corn and wheat prices of \$2.31/bu and \$3.20/bu, respectively. With 2004 prices estimated, these prices were the loan-adjusted 10-year historical average harvest-time crop prices for NW Kansas. N fertilizer was valued at its 10-year average of \$0.225 per lb of N (assumes that typical N fertilizer is half anhydrous ammonia, and 1/4 each of urea and UAN). P fertilizer was valued at its 10-year average of \$0.250 per lb of P₂O₅ (assumes half of the P fertilizer comes from a liquid 10-34-0 formulation and the other half from an 18-46-0 formulation). Because we wanted our models to represent reality, we considered cases where profits associated with optimal fertilizer rates were insufficient to cover application costs, resulting in a recommended fertilizer rate of 0. We assumed a P application charge of \$3.76/acre,

which is the average of 2003-reported NW Kansas custom rates across liquid and dry. The N application charge was assumed to be the average of the anhydrous ammonia application charge and the P application charge just noted, resulting in \$5.13/acre. Finally, recognizing likely cost reductions associated with dual application, we arbitrarily assumed a joint P and N application charge equal to the N application charge, plus half of the P charge, resulting in \$7.01/acre.

Are the yield models as expected?

The first relevant question is, Do the model-recommended profit-maximizing fertilizer rates sufficiently match up with those provided by K-State fertilizer recommendation formulas, where examples were given in Figures 1 and 2? Figures 3 and 4 visually provide that match-up assessment. It is easy to see in Figure 3 where the model's recommended *fertN* rates drop to 0 to reflect situations where returns to fertilizer are insufficient to cover application charges. Interestingly, in Figure 4, it can be seen that the model's 0 *fertP* rate matches very closely to the 0 *Prec* recommended by KSU. Notice that, when looking at *STN*, we assumed an *STP* level of 16 ppm, and when looking at *STP*, we assumed an *STN* level of 40. *OM* was assumed to be 1.6% in either case.

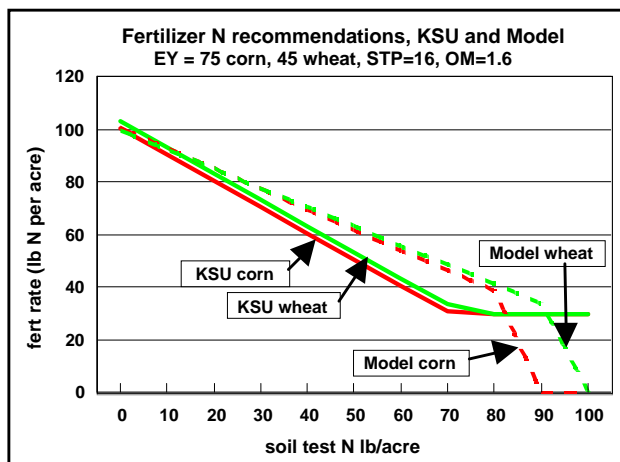


Figure 3

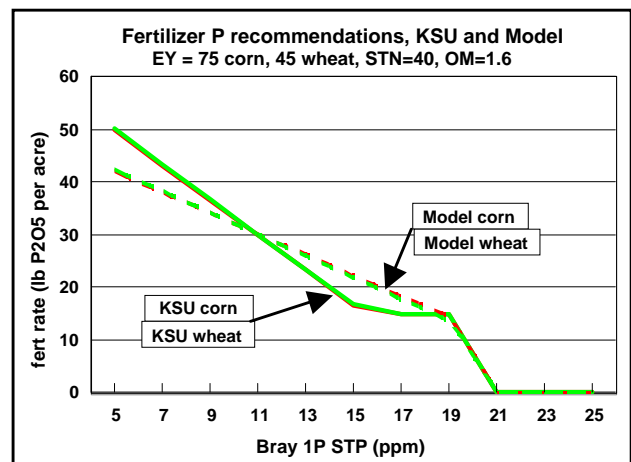


Figure 4

Yield response to fertilizer

Given the earlier discussion around *STP*, Figure 5 shows the expected yield response to *fertP* at different levels of *STP* for wheat. The potential benefit to having higher levels of *STP* is clearly seen in the figure, as is the nearly 0 response to *fertP* at *STP* = 20, which is implied by KSU's recommendations. Figure 6 shows the expected yield response to *fertN* at different levels of *STN* for corn. Though yields eventually plateau, corn yield responds to *fertN* even at relatively high levels of *STN*, such as at 70 lb N/acre.

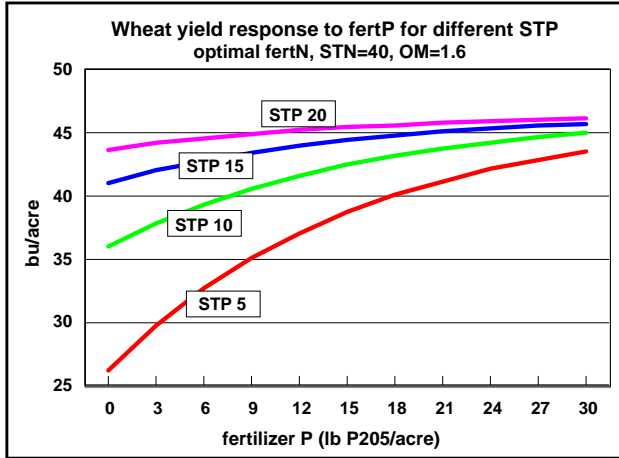


Figure 5

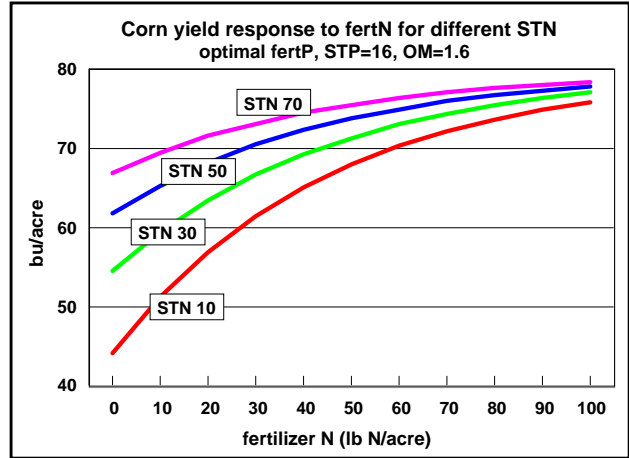


Figure 6

Does it pay to learn soil fertility information?

As noted, it is likely that many farm managers apply the “usual” fertilizer rate from year to year, whatever that is. If we take “usual” to mean that implied by a typical soil test, then we can use the yield models to answer questions like, How much does my profit change if the true soil test is different from my expected soil test? Given the crop and fertilizer prices reported above, along with the expected yields of 45 bu/acre for wheat and 75 bu/acre for corn, Figure 7 shows how profit varies when the true *STN* value is something different than an expected value of 40 lb N/acre (*STP* and *OM* are held constant at 16 ppm and 1.6%, respectively). The expected soil test level is what the fertilizer decision is based on. Note that, when the actual and expected soil tests are equal, our profit benchmark is \$0.

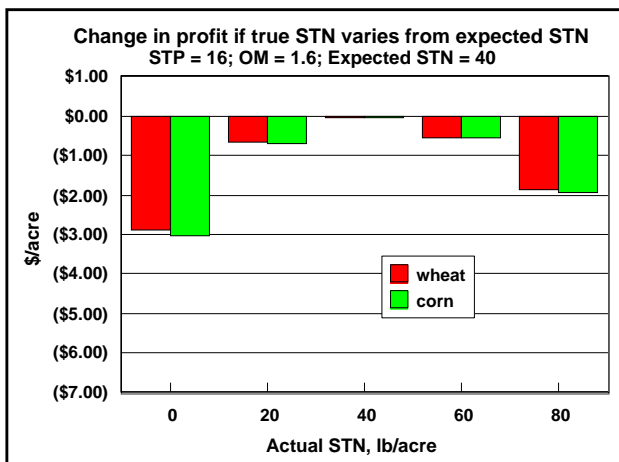


Figure 7

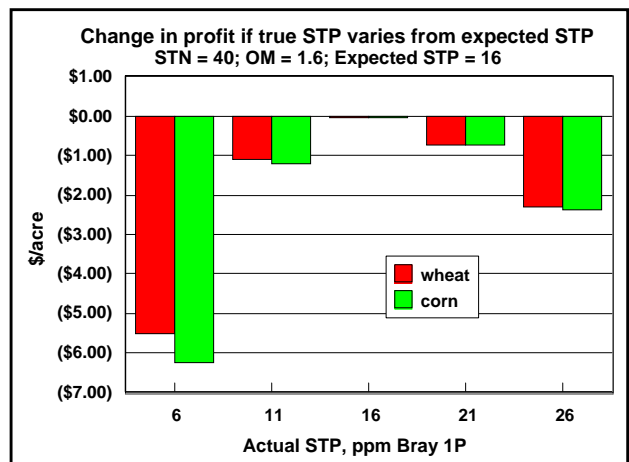


Figure 8

Figure 7 shows that especially large losses occur when true *STN* is a lot lower than expected, which indicates the *potential* benefit to gathering more information about *STN*, such as through a soil test. That is, a manager thinking that *STN* was 40 lb/acre would have applied around 70 lb/acre when he should have applied over 100 if true *STN* were 0, for example. On the other hand, if true *STN* were much higher than he thought, say 80 lb/acre, then he applied 70 lb/acre *fertN*

when he should have applied only around 40 lb. Clearly, the cost of misapplication of fertilizer is not as large for over-fertilization as it is for under-fertilization, and likely the reason farmers often would rather err on the side of applying too much fertilizer. This is important given that the frequency of true soil tests being below their average is generally greater than the frequency of being above their average.

Figure 7 shows that managers should especially consider soil sampling in years when *STN* might be expected to be much lower or higher than average. A wet 2004 summer for much of the Great Plains is one such year. Heavy rains likely leached out or denitrified a substantial amount of nitrogen. This suggests that soil sampling for N could be especially important for the 2005 wheat crop. But, the reverse might be true in especially dry years, when residual N could be much greater than average. Either way, soil sampling for N in such years should be especially profitable. Figure 8 shows information comparable to Figure 7, only for P rather than N. Again, the potential for gains from soil testing is obvious, especially when soil tests are much lower than expected.

While Figures 7 and 8 revealed the *potential* returns to soil sampling, we would need to examine a whole distribution of plausible soil tests before we could quantify our *expected* returns to soil sampling over many fields and many years. To better understand this, we used the 10,000 simulated fields to test how a single fertilizer rate across the 10,000 fields (that rate based on average soil tests) would compare in terms of profitability with assigning the proper rate to each field. Fundamentally, this would be like a farmer who has a good idea about average fertilizer rates over time and space, and then wants to apply that average N and average P rate across all of his fields. Then, he asks the question, What might I gain by taking a single multi-point soil sample from each field, sampling for *STN*, *STP*, and *OM*? Figure 9 answers that question regarding gross returns to soil sampling, splitting out the information between N and P. Essentially, Figure 9 is the inverse of Figures 7-8, only it is an average across 10,000 fields, and where 0 fertilizer was assumed when returns were insufficient to cover application charges.

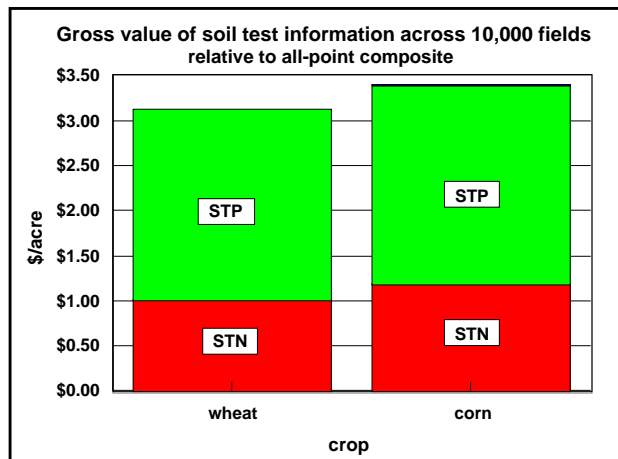


Figure 9

Figure 9 reveals that the value of P information likely is greater than that of N information. The figure shows an average gross return (before subtracting laboratory fees) to soil sampling of \$3.26/acre in this setting where expected wheat and corn yields are 45 and 75 bu/acre, respectively. But what is the cost of such sampling? KSU's June 2004 charge for laboratory analysis of *STP*, *STN*, and *OM* is \$10.50 for the lab work. CropQuest estimates the labor charge for an area-wide composite sample with no GPS information to be about \$30 per field. Soil labs and universities vary widely in what they consider to be the maximum number of acres that should be represented by a single sample. A few suggest that maximum to be as low as 10 acres and a few suggest it might be as high as 100 acres. Across 9 different labs examined on the web, the average maximum field size was 41 acres. This suggests that the total cost of composite soil

sampling might be around \$0.99/acre, which is from $(\$10.50 + \$30.00) / 41$. Against the \$3.26/acre gross returns, this implies an expected net return to soil sampling of around \$2.27/acre. While this value might seem modest, many expected returns to farm management activities are no greater. In fact, returns to using Roundup-Ready soybeans were typically purported by researchers to be in the range of \$5/acre and that “small” value caused that technology to be nearly universally adopted in only a few years. Thus, if expected soil sampling returns were a great deal larger, it is likely that the soil sampling technology also would be widely adopted overnight. Moreover, in terms of return on investment, soil sampling has an expected return of 229% (from $2.27 / 0.99$).

It is noteworthy that the cost comparisons just described were against the fairly strong benchmark of having an accurate understanding of the farm-wide average soil test. Some farmers likely would lack such an understanding. This economic impact of such a misunderstanding depends upon which direction the miss-informed manager decides to go. If he “goes high” on the fertilizer, applying say, 10% more than the uniform rate recommended by a single farm-wide soil test, the average impact across wheat and corn is around \$0.16/acre to the positive (lowering the value of soil sampling shown in Figure 9 by that amount). On the other hand, if he applies 10% less, as someone who has financial constraints might do, then the returns to soil sampling shown in Figure 9 would need to be raised by about \$0.52/acre. In this example, it appears that “applying 10% extra” fertilizer might be a wise move in the absence of soil sampling. While that might be true, it still begs the question, 10% higher than what?

How do crop and fertilizer prices affect returns to soil sampling?

Profit-maximizing fertilizer rates are based on finding the last unit of fertilizer where the revenue from the resultant increased crop yield is just sufficient to cover the fertilizer unit’s cost. Hence, it is the ratio of fertilizer price to crop price that determines optimal fertilizer rates. When that ratio rises, optimal fertilizer rates fall because it takes more of a bushel to pay for the fertilizer unit’s cost. Similarly, when the ratio falls, higher fertilizer rates are implied. Consequently, higher crop prices might offset the impact of higher fertilizer prices, leaving fertilizer rates essentially constant across increasing fertilizer prices. On the other hand, higher fertilizer prices coupled with lower crop prices will sharply curtail optimal fertilizer rates.

The relevant question here involves the value of soil sampling. Figure 10 compares that value across different combinations of adjustments to crop and fertilizer prices (e.g., an x-axis value of -25%/+25% means 25% lower crop prices and 25% higher fertilizer prices). The center bars of the figure are identical to the values shown in Figure 9. From the figure, it is obvious that fertilizer price, not crop price, mostly drives the value of soil sampling. Generally, going from fertilizer prices 25% below average to 25% above average increases the value of soil sampling by more than \$1.50 per acre. It likely is well known that soil sampling should be more

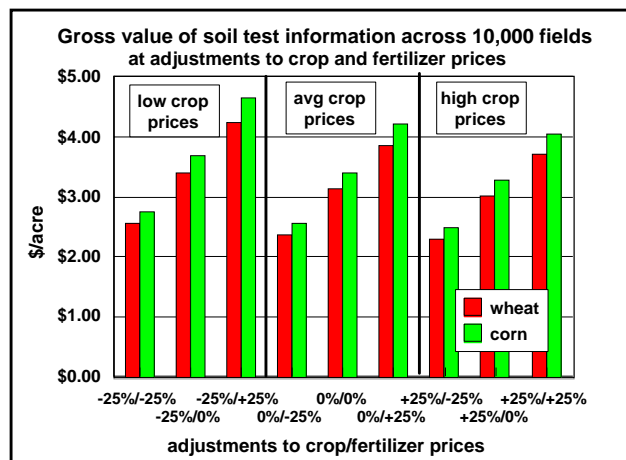


Figure 10

valuable in the face of higher fertilizer prices. The figure helps put a value to that knowledge.

An interesting observations about Figure 10 is that the returns to soil sampling are greater when crop prices are lower. This is due to the fact that returns to fertilizer are less at lower crop prices. Hence, more fields would see recommended fertilizer rates whose returns are insufficient to cover the cost of application, which means that more fields would not need to be fertilized. The manager who merely applies the farm-wide rate on all fields would miss this opportunity to profit from a savings in application costs. This is a reminder that returns to soil sampling come from both applying the correct rate – and not applying at all when returns are insufficient to cover application costs. Note that, if application costs were 0, then the returns to soil sampling would be greater at higher crop prices, rather than lower as shown here.

How many sampling points for an economically worthwhile composite soil sample?

Acquiring soil sampling profits is not automatic. Earlier we had noted the importance of proper sampling depth. Now, we note the importance of pulling soil from enough points (locations) across a field to acquire a reliable bulked soil sample for laboratory analysis and which can be considered representative of the field. To learn about the cost of inadequate sampling, we merely considered our 10,000 fields to be 10,000 locations in a single field. Then, we could “sample” different numbers of random points, repeating numerous times to ensure reliability in our findings (the sample average determined the simulated fertilizer rate for the field).

Figure 11, which shows the results of our exercise, makes it clear that pulling soil from only 5 points in a field might very well negate much of the net gains to soil sampling depicted in Figures 9 and 10. In general, the losses relative to a 10,000-point composite diminish rapidly as sampling point numbers rise. Without further analysis, it appears that a good rule of thumb might be to pull a sample from a minimum of 15 points in the field. It should be noted that, when we speak of sampling from a certain number of points, we mean pulling several cores (say, 5) from within a tight radius (say, 5 feet) of each sampling point. If only a single core were to be pulled at each location, then the losses associated with inadequate sampling would be even worse – because of what is referred to as small scale variability (e.g., taking a core in an old fertilizer band).

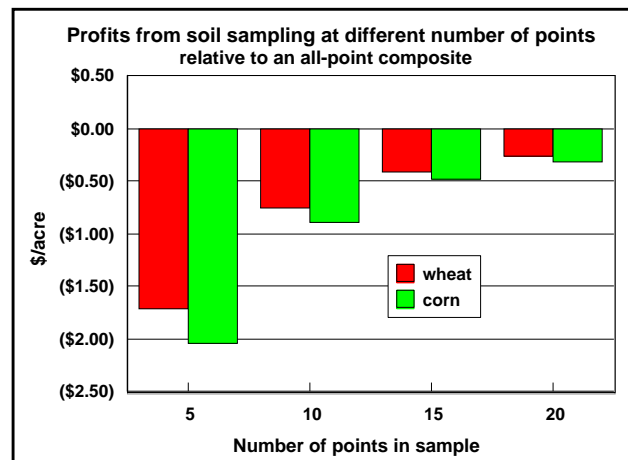


Figure 11

Managing STP over time

Although we briefly discussed the idea earlier, up to now we have not quantified issues associated with managing soil fertility over time. Although the lime/pH decision is generally understood within the context of time, a potentially interesting decision more specific to the Great Plains pertains to P. In particular, KSU’s sufficiency P recommendations and the yield model displayed

in Eq. 4 imply a yield response to both *fertP* and *STP*. If we have a reasonable understanding about how *STP* changes with excess *fertP*, then we can answer the question, What do the yield models imply about managing *STP* over time in order to maximize profits associated with some multi-year time period? Following KSU’s MF-2586 fertilizer recommendations publication, we assume the simple *fertP*-to-*STP* transformation rate of 18 lb/acre of excess P_2O_5 to increase *STP* by 1 ppm.

Although the yield model specified by Eq. [4] may not be exactly the correct mathematical form for describing crop response to fertilizer and soil fertility, it is true that the optimal fertilizer rates implied by the estimated models do closely mimic KSU’s fertilizer recommendations – as seen in Figures 3 and 4. Thus, the economic implications of the yield models should be considered believable by those who consider KSU’s fertilizer recommendations believable. Focusing on P, if this is not true, then KSU would need to reassess its P-sufficiency recommendations, which have evolved through decades of assessment and analysis, and which have for the most part not materially changed for decades. Alternatively, KSU would need to reassess its assertions about how excess *fertP* is transformed to *STP*.

For low-testing soils, KSU’s *Prec*’s (or the optimal *fertP* rates from the yield models) are in excess of crop removal P. For example, for corn with a 75 bu/acre expected yield (yield goal of 82.5 bu/acre) and an *STP* of 11 ppm, KSU’s P sufficiency recommendation (as well as that of the yield model – see Figure 4) is 30 lb P_2O_5 /acre, whereas a 75 bu/acre corn crop is expected to remove only 24.75 lb P_2O_5 (from 75×0.33). This leaves 5.25 lb/acre of excess *fertP*, implying an increase in *STP* of 0.29 ppm (from $5.25/18$). Hence, using the annual optimal *fertP* rate (i.e., the sufficiency recommendation) will result in higher crop yields or reduced

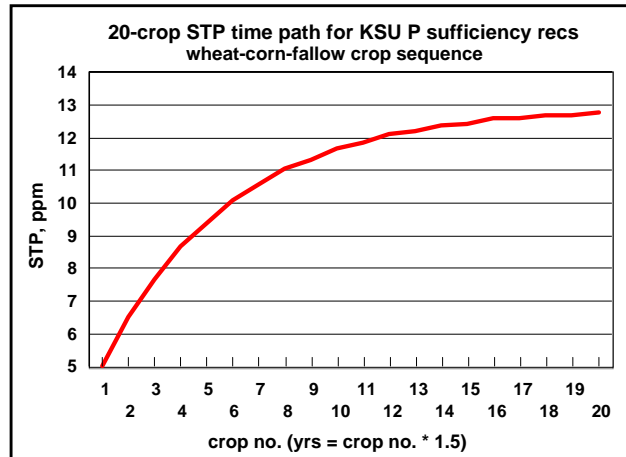


Figure 12

fertilizer costs next year because *STP* will be higher (throughout, we are assuming that *fertN* is determined optimally on an annual basis). That is, optimally managing P one year at a time (using the sufficiency recommendations) will have dynamic implications. In a sense, there is a “free” build component that is inherent within KSU’s *Prec*’s. Based on following KSU’s P sufficiency recommendations and a starting *STP* value of 5 ppm, Figure 12 shows the model-predicted *STP* time path for 20 crops (30 years) in a WCF cropping sequence with the first crop assumed to be wheat. The model predicts *STP* to rise over time, and then equilibrate at the long-run steady state level where *Prec* and crop removal are equal. For the KSU *Prec*’s, the steady-state level is around 13.0 ppm.

In contrast with the *STP* time path following KSU's P sufficiency recommendations, it is useful to show also the paths that would occur following one of KSU's P build programs, that is, 4, 6, or 8 years. Of course, what likely matters most is the economics underlying these different P management programs. To do that we consider a net present value analysis framework, where P is considered an investment whose returns play out over time. Thus, each crop's return (crop revenue less fertilizer cost) must be discounted back to the present. Then, we amortize that net present value back to a constant value per acre per crop so that

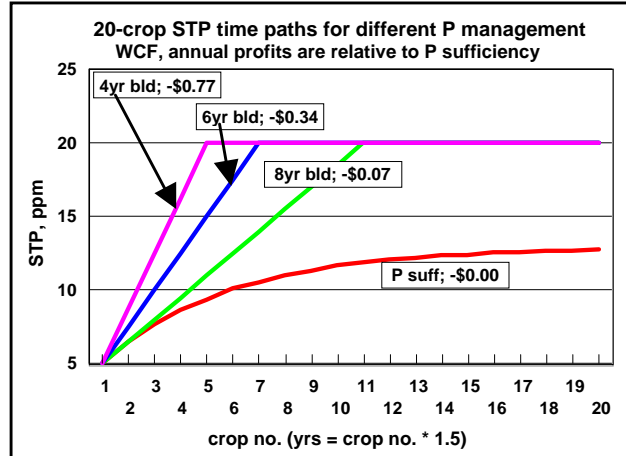


Figure 13

meaningful comparisons can be made. In the underlying financial analysis, we use a bank interest rate of 8% and an income tax rate (federal, state, and self-employment) of 40%. Figure 13 shows the 20-crop *STP* time paths associated with the four KSU P management programs (sufficiency, 4, 6, and 8 year build), along with the profit (\$/acre/crop) for each program relative to the benchmark of the P sufficiency path. Note that, since land is assumed cropped 2 out of each 3 years, we have chosen to present information on a per-crop basis. Annual returns would be approximately 2/3 of reported values, but so would annual investment in fertilizer, soil sampling, etc.

Notice in Figure 13 that, across the 20 crops examined (30 years), all three of KSU's P build programs are expected to have lower returns than KSU's P sufficiency program. The 8-year build, at -\$0.07, came the closest to the P-sufficiency profits. Apparently, even for long forward-looking horizons such as 20 crops, the 4-, 6-, and 8-year build programs build up *STP* "too fast" to be more profitable than merely following KSU's sufficiency recommendation. In a sense, they do not adequately exploit the free build offered by the sufficiency program. As it turns out, although not shown, a 9-year build program would be slightly more profitable than the sufficiency program over 20 crops (\$0.02/acre/crop greater profit). Put another way, the time horizon of interest would have to stretch beyond 20 crops for a manager to expect to garner greater profits with the 8-year build program than with the sufficiency program. The situation is much worse for the shorter build programs. For example, the 6-year build does not become more profitable than the sufficiency program unless time horizons are greater than 30 crops (45 years) and the 4-year build unless time horizons are greater than 50 crops (75 years). Even then, the profits relative to the sufficiency program are very modest, at only a few cents/acre/crop. The reason that the fast build programs are not economically competitive is because of the high cost up front relative to small benefits that occur over many years.

The relative profitability results of Figure 13 make it clear that farm managers should carefully consider how they use the P build programs in MF-2586. For example, they may not be willing to consider the extremely long horizons needed to make the build programs pay. In an effort to uncover situations when the P build programs might be profitable over shorter time horizons, we used our models to examine several other scenarios. First, we had assumed that excess *fertP* applied to this crop only impacts the *STP* for the next crop. When we changed that assumption to reflect the possibility that excess *fertP* impacts the current *STP* level (i.e., instantaneous

transformation), our results changed only marginally. Second, we considered that, once *STP* levels are at the critical level (20 ppm), it could be profitable to skip a year or two of P fertilizer, recognizing the gains to an application savings. Recall that we earlier had assumed a \$5.13 N-only application charge and a dual application charge of \$7.01, for a savings in P application charges of the difference, or \$1.88/acre whenever 0 P was applied. But, this also was insufficient to change our results. The model predicted that the yield sacrificed in the year of no *fertP* (along with the yield lost the following year due to a drop in *STP*) was too great to be offset by savings in application charges. Thirdly, we considered the possibility of a higher or lower critical level than the 20 ppm assumed by KSU in its build program. This did help. In fact, with the 20-crop situation, starting at *STP* = 5, and a 6-year build, the optimal target turned out to be 15 ppm rather than 20 ppm. In that case, the build program would have netted about \$0.16/acre/crop more than the sufficiency program. But, with the same situation and a 4-year build, it was impossible to pick a critical *STP* level that caused the build program to be more profitable than the sufficiency one.

Following the preceding discussion, one might wonder whether it really pays to build up *STP*. Again, that question can be answered with our yield model. In particular, we asked the following questions. In an infinite horizon, what is the optimal build strategy? Then, how does the profitability associated with 20 crops compare to the same 20-crop profitability already discussed. Figure 14 adds this information to the preceding figures, making it clear that there is an optimal build strategy given the situation, and it is \$0.38/acre/crop more profitable than the sufficiency program.

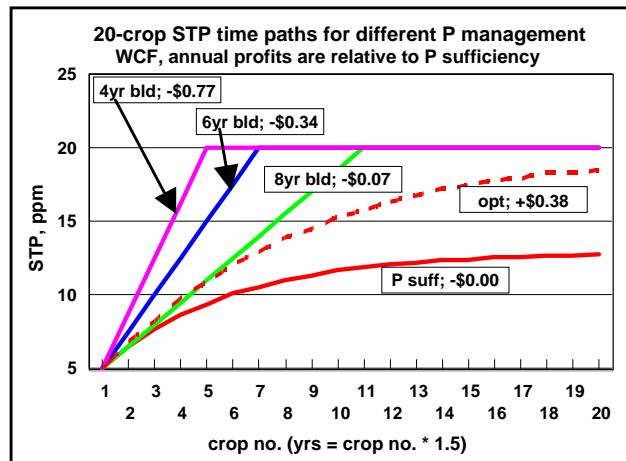


Figure 14

It should be noted that the model-determined 20-crop optimal *STP* path shown in Figure 14 was not a true optimum given that a manager actually knew that his time horizon would end at the end of 20 crops. In that case, the manager’s profit maximizing strategy would be to “back off” on *fertP* the last few years since he knows he will not be able to capture the benefits of higher *STP* in future years. In this fairly long horizon of 20 crops, this particular consideration was not that great and resulted in only another \$0.07/acre/crop over that shown with the “opt” line in Figure 14. Nonetheless, this feature would be potentially much larger in short horizons – especially if one were to consider land with high rather than low *STP*.

In the case of considering an *STP* build, the land tenant’s problem is somewhat different from the landowner’s. In particular, rental contracts are often short (e.g., 1-3 years), suggesting that it would be profitable to “mine” P from high-testing soils and certainly “not build very much, if at all” low-testing soils. Yet, short term rental contracts are often renewed, leaving the P-mining tenant with low-*STP* at the start of the renewed contract. Thus, for a land tenant wanting to consider the tradeoff between the benefits of higher *STP* and the risk of contract renewal, it might be appropriate to consider something like a continuously moving 10-year horizon. Each year, the tenant would apply the *fertP* rate appropriate for the first year of a 10-year contract. We used our model to examine this strategy over the 20 crops discussed earlier. Though not reported, the

associated *STP* time path was a little lower than the “opt” one of Figure 14, and the relative profits were within \$0.02 of those shown with “opt” in the figure.

All in all, it appears that KSU’s new P build recommendations in MF-2586 are inappropriate for anything but fairly long time horizons. And, even with long horizons, it is likely that profits can be enhanced significantly by programs that are not based on a fixed amount of build each year. Hopefully, upcoming research at KSU will eventually rectify this situation, with recommended P build rates ultimately being based on a user-specified time horizon – so that they can result in an *STP* time path and profits more like those shown in the “opt” line of Figure 14.

An important aspect to improving on KSU’s P build programs is more accurate and site-specific determination of the appropriate P_2O_5 to *STP* transformation rate. The value of 18, used in KSU’s current build recommendations, is well supported in the research literature from many years and many areas of the U.S. On the other hand, there also has been considerable research, most notably from Montana, Canada, Nebraska, and Colorado, that suggests the transformation rate could be dramatically lower, perhaps around 6. Though not shown, when we made this assumption in our simulations, fast build programs became especially attractive. For example, the 4-year build was \$1.52/acre/crop more profitable than the sufficiency program (still considering a 20-crop amortized value). And, the infinite-horizon optimal strategy, which tended to build even faster and to a critical *STP* level of around 26 rather than 20, was \$1.76/acre/crop more profitable than the sufficiency program. Thus, it is critical that an improved understanding of the transformation rate emerges from continued research.

STP and land values and rents

The preceding discussion around managing *STP* over time has significant implications for rental rates and land values. To examine this issue, we used the various assumptions and models already discussed to examine scenarios around different levels of *STP* and different time horizons. In this case, a 3-year time horizon is considered to be a true 3-year horizon, where it would be most profitable to mine P from high-testing soils because the tenant actually knows he will lose the land after 3 years. Also, up to now, we have compared values on a per-crop basis. Yet, because cash rent generally is paid on an annual basis, we had to decrease our per-crop values by 1/3 to account for our assumption of 2 crops in 3 years. The results of this analysis are displayed in Figure 15, which depicts rental premiums and discounts associate with *STP* level for a wheat-corn-fallow crop rotation in NW Kansas. Rent premiums should be compared to a typical annual rental rate in the area of around \$32.50/acre.

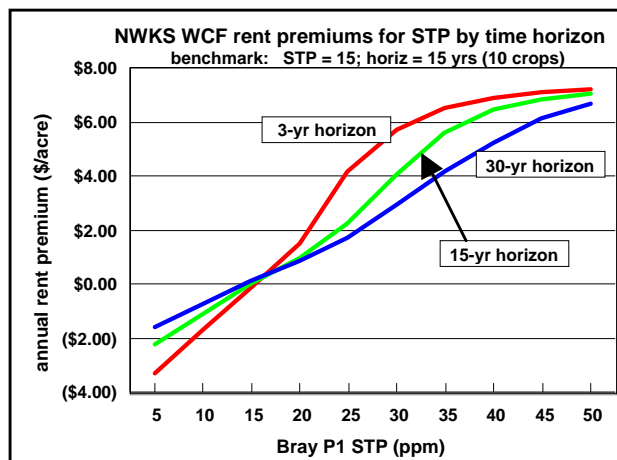


Figure 15

In a true 3-year rental contract, *STP* is especially important. High *STP* means no *fertP* would need be applied for maximizing profits. Alternatively, low *STP* means high *fertP* rates to maximize

profits, but the tenant will not benefit from the *STP* build he will have caused – the next tenant reaps the rewards. Consequently, in a true 3-year contract, the tenant could pay as much as \$4.21/acre more rent for land that has an *STP* level of 25 ppm as compared to the more usual level of 15 ppm. Yet, the same 3-year tenant should pay \$3.29/acre less rent for land that has an *STP* level of only 5 ppm. Even with a 15-year contract (closer to how long land tends to be rented in NW Kansas), 25 ppm soils are worth about \$2.28/acre more annual rent than 15 ppm soils, and 5 ppm soils should be discounted about \$2.23/acre.

Soil testing and precision agriculture

Generating profits from soil testing is always based on the tradeoff between informational costs and the expected benefits arising from that information. For example, basing fertilizer rates off of the usual 15-point field composite sample implies that the soil sample is used as merely a reasonable predictor for all points in the field. Moreover, it is about the tradeoff between costs and benefits of informational sources that may have different degrees of accuracy. Hence, for example, a site-specific grid soil sample likely (but not necessarily) will provide a more accurate map of a field's soil fertility than will a field composite. But, that grid map will come at a higher cost than the simple field-wide composite soil sample. Also, considering soil properties in precision agriculture may be about using proxies for soil tests (e.g., electrical conductivity, remote sensing, crop yields). Such proxies are expected to be less accurate than actual lab-based soil testing, but might still be more profitable since they may have lower costs.

For this part of the analysis we consider a somewhat different simulated data set than the 10,000-field data used up to now. In particular, we consider a 100-acre square field, with each acre comprised of 64 equally-spaced data points (6,561 points with borders), where *STP*, *STN*, and *OM* soil properties have the same averages as before (16 ppm, 40 lb/acre, and 1.6%, respectively), but where a particular soil property tends to be spatially dependent. More importantly, we considered a degree of spatial dependency believed appropriate for many agricultural fields in the Great Plains and even in the Corn Belt. More simply put, in a spatially dependent framework, high-testing areas of the field tend to be clustered, as are low-testing areas, etc.

In our spatial simulations we also considered a small tendency for different points in the field to have higher/lower yields due to intrinsic differences in soil properties other than the three measured soil properties. For the 100-acre field we assumed 1-acre management, where yields and fertilizer rates can only be discerned down to a 1-acre scale. That is, though fertilizer rate and combine yield monitor information may be collected at a finer scale, that information is assumed to be aggregated to 1-acre cells. Site-specific grid soil sampling (GS) was simulated at the 1-acre and 4-acre scale, with the average of the two results considered as representative of the usual 2.5-acre grid sampling program. Twenty future crops of a WCF rotation (i.e., 30 years) are considered in this analysis, but only in a short-run framework, where each crop's fertilizer decisions are based on a 1-crop time horizon (i.e., P is not considered to be managed over time). Finally, it is important to note that we tried to mimic real-life errors in information. For example, wheat and corn yields are simulated with an intrinsically large error about them that is similar to real-life yield modeling errors. Where used, crop removal of P and N is estimated with a rather large error as well, similar to what might be expected when farm managers use previous-year expected soil tests, along with known current-year fertilizer rates and crop yields, to predict next-year's soil test

level.

What follows is a listing of the soil information scenarios considered in this research.

FCmp-1c

This scenario assumes that the usual field composite soil sample is taken ahead of each crop (hence *1c*). We assume 16 equidistant points of the 6,561 total are sampled (5 cores at each point) within the field and subsequently sent into the soil testing laboratory as a single sample (for each of *STP*, *STN*, and *OM*) for the field. That single sample would lead to a single fertilizer (i.e., uniform) rate for each of *fertP* and *fertN*. This scenario is analogous to the field composite sampling considered around previous figures in this paper. For the 100-acre field, one soil sample is assumed analyzed by the laboratory each year.

GSCent-1c

This scenario assumes that only the centroid of each 2.5 acres is sampled each year. Then, that centroid value is assigned to the 2.5 acres that it centers. For the 100-acre field, 40 samples (i.e., 100 acres / 2.5 acres per sample) are assumed analyzed by the laboratory each year. Variable rate application (VRA), with 1 rate for each 2.5 acres, is considered necessary to implement this scenario – as it is for all of the remaining scenarios. As a reminder, we actually considered 1- and 4-acre soil testing – since 1 and 4 acres work out symmetrically in the 100-acre field (either a 10x10 grid of cells, or a 5x5 grid). Though a 2.5 acre cell would not work out to a symmetric representation, our discussion proceeds as though it does – since what is most relevant is the economics.

GSID4-1c

Like *GSCent-1c*, this scenario also depends on grid sampling 40 centroids each year. However, a common spatial interpolation technique (inverse-distance to the 4th power, hence *ID4*) is used to predict all data points in the field, with the predicted points in a 2.5 acre area being averaged to result in an expected value for that 2.5 acres.

GSCmp-1c

Like the preceding two scenarios, this scenario also assumes 40 lab samples each year. Only here, the sample for a particular cell is considered to be a composite of 16 points within the cell. The composite sample value for a cell is then assigned to all points in that cell. Notice that this scenario would be more expensive than *GSCent-1c* or *GSID4-1c* – since the sampling manager would have to walk around in the 2.5 acres to pull samples rather than pull them from only the cell's centroid.

GSCmp-5c

This scenario is the same as *GSCmp-1c*, except that grid sampling is considered to occur only before each 5th crop (hence *5c*). During each of the other 4 years a field composite sample is assumed, which is used to proportionally adjust the cell-specific predictions for those years. That is, for the first crop, 40 samples are analyzed, with each sample's values being used to determine cell-specific fertilizer rates for that year, as well as predictions for next year's cell-specific values (relies also on cell-specific yields and cell-specific fertilizer rates to get at expected crop removal of fertilizer). Then, next year's predicted cell-specific values are proportionately adjusted up or

down so that an average across all 40 cells equals the average of the field composite. Then, for the sixth crop, the grid sampling is assumed to occur again, and so on.

GSCmp-10c

This scenario is functionally the same as *GSCmp-5c*, except that the grid sampling is assumed to occur only before each 10th crop (hence *10c*). Again, crop removal is used to predict soil tests in the off years, along with a field composite sample for adjustment.

Ent-1c

This scenario assumes entropy (hence *Ent*) is used, along with the yield model and yield monitor and fertilizer rate information, to estimate each acre's soil test values (hence, each 2.5 acre cell value). Additionally, as with others, these estimates are conditioned on (proportionately adjusted to) a field composite soil test each year – to preclude straying too far from a composite sample's value

ECM-1c

ECM stands for medium electrical conductivity, as in Veris information. However, it really represents any sensor-based information source with a set degree of accuracy. For medium accuracy we assume the following correlations of instrument readings to soil tests: *STP* 0.70, *STN* 0.30, and *OM* 0.60. These correlations are from what has actually been observed on the Kastens farm in NW Kansas. Hence, they likely are reasonable accuracy levels to consider. For *1c*, the instrument is considered used for each crop.

ECM-5c

This scenario is the same as *ECM-1c*, except that the sensor information is assumed collected only ahead of each 5th crop. In the off years, as with several of the other scenarios, calculations of crop removal of fertilizer are used for the cell-specific predictions of soil test values, which are then conditioned on a field composite sample.

ECM-10c

This scenario is the same as *ECM-5c*, except that the sensor information is assumed collected only ahead of each 10th crop.

ECL-1c

This scenario is like *ECM-1c*, only less accuracy is assumed for the sensing device. In particular, we arbitrarily consider correlations that are 30% lower than those for *ECM*. Hence, assumed correlations are *STP* 0.49, *STN* 0.21, and *OM* 0.42.

ECL-5c

This scenario is the same as *ECL-1c*, only that the sensor-based information is assumed to be collected ahead of only every 5th crop. Cell-specific predictions are conditioned on the field composite measure in the off years.

ECL-10c

This scenario is like *ECL-5c*, only the information is considered collected only every 10 years.

ECH-1c, ECH-5c, ECH-10c

These scenarios are the higher-correlation (30% higher than the *ECM* measures) counterparts to the *ECL* and *ECM*. Hence, assumed correlations are *STP* 0.91, *STN* 0.39, and *OM* 0.78.

Figure 16 shows the potential benefits for each of the scenarios examined. They are *potential* benefits because no informational costs are considered in this figure, only the “yield revenue less fertilizer cost” values associated with the different informational regimes. Several features of Figure 16 are worth noting. First, the annual field composite scenario (*Fcmp-1c*) shows \$3.26/acre/crop as a potential benefit over some farm-wide knowledge of soil test. This is the same \$3.26 that was discussed earlier around Figure 9, which showed the benefits to soil sampling using a field composite over mere knowledge of a multi-field farm average soil test. Second, the potential benefit from merely assigning an annual point sample’s value to each 2.5 acres (*GSCent-1c*) is smaller than even a field composite sample. Moreover, using inverse-distance to the 4th power to interpolate between centroids helps the situation, but not much (*GSID4-1c*). On the other hand, taking an annual composite sample from each 2.5 acres (*GSCmp-1c*) is among those regimes with the greatest potential to enhance profits by using site-specific soil information. Some potential benefit is sacrificed when the 2.5 acre composite is taken only every 5 crops (*GSCmp-5c*) or every 10 crops (*GSCmp-10c*), but less frequent grid sampling would be much less costly. The mainly yield-monitor-based *Ent-1c* method offers less potential benefit than many of the other regimes, but it likely would be less costly since it is based mainly on numerical calculations and a field-scale annual composite sample. Finally, the sensor-based regimes (those preceded by an *EC*) suggest substantial benefit, especially when the sensors are assumed used annually (the *1c* ones). Surprisingly, using sensors that are much more accurate (compare *ECH* ones to *ECL* ones) does not seem to largely enhance the potential benefits.

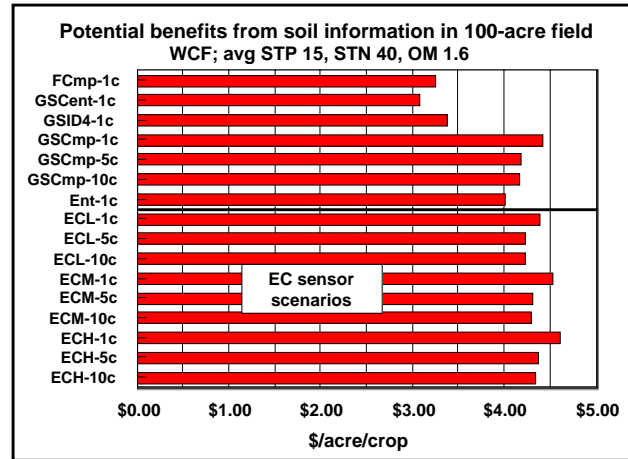


Figure 16

While Figure 16 shows potential benefits from using soil information technologies, these technologies come at a cost. But, devising meaningful and accurate estimates of such costs is difficult at best. In particular, observed custom charges early in a technology’s life tend to be much higher than what ultimately evolves over time. Or, what essentially is the same thing, ever more services are provided over time, for a cost that remains relatively flat (e.g., think of the purchase cost of a computer over time). Likely, that is due to uncertainty about potential business for the service provider and to the fact that customers are few and far between. Thus, early on, not only are the fixed costs of capital outlays spread over only a few acres, but the variable cost for servicing those acres also are high – because customers only want “a field or two” treated and this implies a relatively large travel distance between customers’ fields. As an example, Whipker and Akridge’s annual dealership survey reported a cost for site-specific soil sampling of \$7.30/acre in 2002 but only \$5.91/acre a mere two years later in 2004. Similarly, the charge for multi-product VRA of fertilizer dropped from \$7.67/acre to \$6.95/acre during the same time interval. Because, the decision to invest in site-specific soil information technologies likely is a long-run decision,

we wish to be more representative of what we think will be than what currently is.

For our purposes here, we divide informational costs between field work and office work. Field work is considered to be labor and the costs of equipment usage to collect information. Office work is considered to be labor and costs of computer and software for analyzing data. For the office work part of each informational regime shown in Figure 16, except for *Fcmp-1c*, we arbitrarily assume \$1/acre/crop.

Based on field time information from a service provider, we believe that the labor portion of centroid-based 2.5 acre grid sampling is around \$0.60/acre. Arbitrarily considering that labor represents 60% of the total field cost (equipment expenses for the balance) brings the total field cost to around \$1/acre. Thus, given expanded use of grid sampling and increased competition, we believe that the field work costs of such grid sampling might fall to that number; or, if not, that services provided for the fee charged will expand greatly. Thus, we assume a total charge for the 2.5-acre centroid-based grid sampling scenario to be \$2/acre/crop (\$1/acre for the field work and \$1/acre for the office work). Though this charge is decidedly lower than what is currently charged for such activities (\$5.91/acre), we believe it to be a more meaningful characterization of such costs for decision making. In considering composite-based grid soil sampling, we obtained information from a service provider regarding the additional labor needed to walk around the 2.5 acre cell, collecting soil cores, rather than merely collecting them at the cell's centroid. The additional labor amounted to around \$1.50/acre. Hence, for the composite-based grid soil sampling scenario, we assume a charge of around \$3.50/acre inclusive of the \$1/acre office work.

For the sensor-based technologies (use of an electrical conductivity machine such as Veris is our example) we consider the cost per operation to be \$3/acre, which is based on the idea that custom charges for other such light-draft farm implements likely would be similar. Adding in the \$1/acre for office work brings the total EC charge to \$4/acre, which is perhaps \$1 to \$2 per acre less than what typically is charged for that service today. Based on information from a service provider, we assume the field cost of a field composite sample is \$30. The soil testing laboratory fee is assumed to be \$10.50 per sample analyzed, except that, because of the additional volume of business, the lab fee for grid samples is assumed to be 10% less, or \$9.45/sample. Since yield monitors are becoming ever more commonplace, whether or not a farm uses site specific soil information, we assume no cost differences among information scenarios associated with yield information. Similarly, since we believe VRA equipment soon will be commonplace among farms and fertilizer applicators, resulting in no distinction between uniform and variable application charges, we made no special consideration for VRA charges across information scenarios. Each of the costs just discussed were appropriately assigned to each of the soil information scenarios. For reference, the cost and benefit information is recounted in Table 2.

Table 2. Cost information for precision ag examples

	cost of						cost of			cost of			Fig. 16	Fig. 17
	# of field	cost of	field comp	# of grid	# of grid	cost of	grid cent	grid comp	# of EC	cost of EC	cost of	office work	gross	net
	comp	lab tests	field work	centroid	comp	lab tests	field work	field work	runs	at \$3.00 per	at \$1.00 per		information	information
	samples	at \$10.50	at \$30.00	samples	samples	at \$9.45	at \$1.00	at \$2.50	per crop	acre/run	acre/crop	total cost	benefit	benefit
	per crop	per sample	per sample	per crop	per crop	per sample	per acre	per acre	per crop	(\$/crop)	(\$/crop)	(\$/a/crop)	(\$/a/crop)	(\$/a/crop)
<i>FCmp-1c</i>	1	\$10.50	\$30.00									\$0.41	\$3.26	\$2.85
<i>GSCent-1c</i>				40		\$378.00	\$100.00				\$100.00	\$5.78	\$3.08	(\$2.70)
<i>GSID4-1c</i>				40		\$378.00	\$100.00				\$100.00	\$5.78	\$3.38	(\$2.40)
<i>GSCmp-1c</i>					40	\$378.00		\$250.00			\$100.00	\$7.28	\$4.43	(\$2.85)
<i>GSCmp-5c</i>	0.8	\$8.40	\$24.00		8	\$75.60		\$50.00			\$100.00	\$2.58	\$4.20	\$1.62
<i>GSCmp-10c</i>	0.9	\$9.45	\$27.00		4	\$37.80		\$25.00			\$100.00	\$1.99	\$4.17	\$2.17
<i>Ent-1c</i>	1	\$10.50	\$30.00								\$100.00	\$1.41	\$4.01	\$2.60
<i>ECL-1c</i>									1	\$300.00	\$100.00	\$4.00	\$4.39	\$0.39
<i>ECL-5c</i>	0.8	\$8.40	\$24.00						0.2	\$60.00	\$100.00	\$1.92	\$4.24	\$2.32
<i>ECL-10c</i>	0.9	\$9.45	\$27.00						0.1	\$30.00	\$100.00	\$1.66	\$4.23	\$2.57
<i>ECM-1c</i>									1	\$300.00	\$100.00	\$4.00	\$4.54	\$0.54
<i>ECM-5c</i>	0.8	\$8.40	\$24.00						0.2	\$60.00	\$100.00	\$1.92	\$4.32	\$2.40
<i>ECM-10c</i>	0.9	\$9.45	\$27.00						0.1	\$30.00	\$100.00	\$1.66	\$4.30	\$2.64
<i>ECH-1c</i>									1	\$300.00	\$100.00	\$4.00	\$4.61	\$0.61
<i>ECH-5c</i>	0.8	\$8.40	\$24.00						0.2	\$60.00	\$100.00	\$1.92	\$4.37	\$2.45
<i>ECH-10c</i>	0.9	\$9.45	\$27.00						0.1	\$30.00	\$100.00	\$1.66	\$4.34	\$2.68

Figure 17 depicts the possible profits associated with the different soil information scenarios. In the figure, notice that the net return associated with a field composite is \$2.85/acre/crop, which is higher than the \$2.27 discussed earlier around Figure 9. That is because there we had assumed a 41-acre composite soil sample, whereas here we are assuming a single composite for the whole 100-acre field. The figure shows that most of the opportunities to profit from site-specific fertility management dissipate in the presence of costs. In particular, given our assumptions, grid soil sampling ahead of each crop is far from profitable for this WCF dryland cropping scenario. Even reducing the frequency of grid sampling to once every 10 crops leaves grid sampling about \$0.68/acre/crop short of the profits associated with a simple annual field composite soil sample. This is especially important today, when custom charges for grid sampling likely are considerably higher than the costs assumed here.

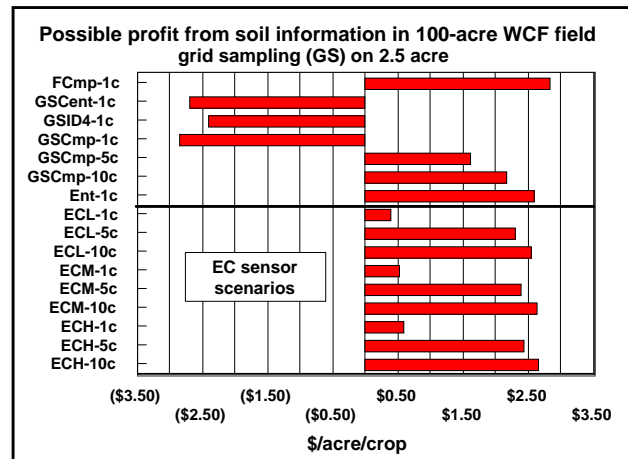


Figure 17

In Figure 17, the *Ent-1c* scenario is only \$0.25/acre/crop short of the profits associated with a field composite soil sample. This is especially encouraging since the \$1/acre/crop office work charge for this program likely is already adequate to cover its costs, especially if computer time and software costs can be spread over several thousand acres each year. Hence, slight improvements in this program likely would make it a viable candidate for site-specific soil fertility management.

A second encouraging information scenario in Figure 17 is *ECM-10c*, which had profits only

\$0.22/acre/crop less than those of the field composite. Functionally, this program “uses a Veris machine” every 10 crops. The accuracy correlations assumed in this program already have been observed on the Kastens farm and so are certainly plausible. Moreover, the \$3/acre operating cost, along with the \$1/acre/crop office charge likely are already reasonable today. Hence, as with *Ent-1c*, slight improvements to this program likely would make it a viable candidate for site-specific soil fertility management. All in all, for this dryland cropping example, it appears that soil test proxy information might be more appropriate than grid soil sampling – especially considering that such information is likely to improve more in terms of accuracy and costs than is grid soil sampling (whose costs have already been largely lowered from current custom charges), which depends heavily on field labor and soil testing laboratory charges.

It should be remembered that the foregoing describes a short-run analysis of site-specific management, where 20 future crops were considered, but where for each crop the optimal decision was based on the assumption that land would be controlled for only one year. Earlier we had shown that managing some soil properties dynamically, for example P, can mean increased profits. Consequently, if site-specific management is considered to be an integral part of long-run dynamic management of P – as it might be, for example, when crop removal rates are computed on a sub-field scale, then it is likely that site-specific management of fertilizer and fertility would indeed be more profitable than a simple field composite soil sample ahead of each crop.

A word about lime and soil pH

Generally, this paper has ignored lime and soil pH in favor of N and P. But, a few words are in order, especially around precision ag’s treatment of the issue, and especially because variable-rate lime often has been among the most profitable precision ag technologies reported in field research across the U.S. Related to soil pH, two site-specific technologies come to mind. First, is the use of home test kits for soil pH that allow for potentially less expensive assessment of soil pH. Second, Veris now offers an on-the-go sensor for collecting spatially dense measures of soil pH. Both technologies have a potential problem in that they do not directly provide recommended lime application rates. After all, this usually is something provided by soil testing labs, where a measure called buffer pH is provided, and which links directly to a lime recommendation.

Fortunately, the inability of the two site-specific soil pH technologies to directly provide lime recommendations is a surmountable obstacle. First, with home test kits, a manager might take a few duplicate soil samples, one for the home test and one for a professional laboratory. Then, the buffering relationship implied by the lab’s lime recommendation (i.e., the amount of lime it takes to change soil pH by a set amount) might be assigned to all of the fields points where only a home test was used. This approach relies on two key assumptions. First, the amount of lime required to change soil pH is constant across different levels of soil pH. That is, if 1 ton of lime increases soil pH from 5.0 to 5.5, then it will take 2 ton of lime to increase soil pH from 5.0 to 6.0. Second, the lime-to-soil pH transformation rate must be constant across different points in the field.

The first of the two assumptions listed above (i.e., a constant transformation rate across differing levels of soil pH) is fairly well supported in the research literature. However, the second assumption likely is inappropriate for many fields. That is, soil’s pH buffering capacity might change dramatically from location to location within the same field. In this case, the manager

might proceed as follows. First, measure soil pH in many locations in the field (either with the home test kit or with a Veris pH sampling machine). Second, apply some fixed quantity of lime to the whole field, say 1 or 2 tons per acre. Third, after sufficient time, perhaps one year, again take site-specific measures of soil pH across the field. Now, site-specific transformation rates can easily be calculated. Then, these site-specific transformation rates can be applied to future measures of soil pH. That is, at least conceptually, the blanket lime application would need to be made only once.

Soil sampling and no-till

No-till crop production brings special considerations to soil sampling. First, in the absence of the usual soil mixing wrought by tillage, distinctively different layers of soil can evolve, even near the soil's surface. This is called stratification. For example, it could be that it would be better to replace the single 0-6 inch soil sample with two separate samples, one for 0-3 inches and one for 3-6 inches. That is especially true for lime/soil pH management, where no-till can exacerbate the drop in soil pH over time in the top few inches, as well as the soil pH increase following a lime application. Also, changes in soil due to tillage practices such as no-till often take years to reach even the 6 or 8 inch depth. Thus, the manager hoping to monitor such changes should consider separate samples for different depths of soil.

Long term no-tillers often tout soil benefits that traditionally have not been measured, for example those associated with structure, pore space, and water conductivity. Moreover, they acknowledge that organic soil fertility components can play a larger role in no-till than in conventional till farming. This means that such organic measures (e.g., organic N rather than only nitrate nitrogen, organic P rather than only *STP*) could become important components of a profitable soil testing program. Popular press articles along these lines are just beginning to appear. And, soil testing laboratories seem to be increasing their offerings of such tests. As with most new technologies, using these novel soil measures will bring increased profit but increased risk for early adopters.

Not surprisingly, studies involving the interaction between soil properties and tillage practices appear to be increasing in number. To gain some understanding of what might be coming in the near future, it is interesting to recount a small sample of the non-standard types of soil information already being collected by researchers in the area. The following examples were found in only one recent issue of the *Soil Science Society of America Journal*.

Soil strength: measured by pre-compression stress and shear strength, an indicator of load bearing capacity

Soil texture: percent of sand, silt, and clay particles

Hydraulic conductivity: measure of soil's ability to carry water and be infiltrated

Bulk density: measure of relevant pore space and potential for holding/conducting water

Aggregate size: indicates pore size and continuity information

Amino sugars: a different fraction of carbon (carbon usually indicated by organic matter)

Mineralizable N: indicator of amount of N that will be mineralized

Organic N: another relevant N component

Microbial biomass: measure of relevant biomass

Humic acid fractions, e.g., N: refining organic measures of interest

Pedality: describes the structure as strength, size, shape, and arrangement of peds (i.e., dry aggregates)

The point to listing the unusual measures above is to indicate that soil testing is far from a dying technique. As no-till increases in frequency, it is likely that some of these measures will become routine soil tests for some farm managers, especially if their informational cost is not high. Moreover, even if such measures formally remain in the research realm, it is likely that sensor-based instruments will continue to evolve that provide proxies for such potentially important indicators of crop production capacity and fertilizer needs in the face of reduced tillage.

Conclusion

Though farmers agree that soil testing provides important information for fertilizer decisions, it is likely that most farmers do not use soil testing on a routine basis. To improve farm managers' fertilizer decisions around informational sources, this paper quantifies expected returns to soil sampling. Although fertilizer recommendations from universities and soil testing laboratories provide useful guidelines for increasing profits with fertilizer, they do not answer important questions such as, How much profit do I sacrifice if I do the wrong thing? Answering such questions relies on mathematical yield models, which depict expected crop yield as a function of soil fertility and fertilizer, as well as of other factors. This paper uses yield models for dryland wheat and corn to examine the returns to information such as that derived from soil testing. Dynamic management of P is also considered.

This research shows that soil testing, especially for N, is likely to be most profitable in especially dry or especially wet years, and in years when fertilizer prices are especially high. In a dryland crop rotation of wheat-corn-fallow, the gross benefit from a single composite soil sample for each field is about \$3.26/acre/crop. The cost of such information is around \$0.99/acre/crop if the maximum recommended field size is 41 acres, but only \$0.41/acre/crop if a 100-acre field is sampled with a single composite soil sample. This leaves net returns to soil sampling on the order of \$2.27 to \$2.85/acre/crop. Though seemingly modest, small but repeatable profits often separate successful from unsuccessful farms over time. Fertilizer prices drive returns to soil testing more than do crop prices. When fertilizer prices rise 25%, net returns associated with soil testing rise around 35%.

Sampling an inadequate number of points in a field can negate returns to soil testing. Fifteen points per field should provide a reasonable compromise between sampling cost and accuracy. Intentionally applying extra fertilizer P each year to build up soil test P in low-testing soils should be profitable, except in cases where land tenancy is extremely short. However, our results suggest that soil test P probably should be built up more slowly than that indicated by a 4-, 6-, or 8-year build program. Land testing especially high in P (e.g., 30 ppm Bray 1P) is worth about \$4.08 more than average testing land (e.g., 15 ppm) in annual rent for the tenant who will control the land for 15 years. Grid soil sampling is no more profitable than a field composite. However, available non-soil-testing fertilizer management programs (e.g., those that depend on soil test proxies) are nearly as profitable as a field composite, and likely would be more profitable in the face of only modest improvements in accuracy or cost – or in the face of long-run P management.

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