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Abstract

Crop producers are increasingly interested in reducing nitrogen use without sacrificing yield. Technology is available for precise application at the sub-field level, but adoption has been sluggish. This paper estimates the relative profitability of a field level annual predictor of mid-season N requirements and a regional predictor of the same.

Keywords: nitrogen needs, nitrogen use efficiency, precision agriculture, wheat

Introduction

Crop agriculture in the United States and other developed nations intensively uses nitrogen fertilizer (N) to increase yields. Expenditures on N account for 28% and 32% of operating expenses for U.S. producers of wheat and corn, respectively (United States Department of Agriculture, 2005). Many researchers have focused on improving the efficiency of N use in agriculture (e.g., Raun and Johnson, 1999; Greenhalgh and Faeth, 2001; Cassman et al., 1998). Raun and Johnson (1999) estimated that only 33% of N applied to cereal crops worldwide is recovered in grain. Traditionally, N has been applied prior to planting at a uniform rate selected to meet a yield goal based on historical yields. However, plant N requirements vary spatially and temporally. For example, Solie, Raun and Stone (1999) show that naturally occurring soil N content varies significantly at scales of approximately 1 m^2. Several studies (e.g., Mamo et al., 2003; Washmon et al., 2002; Lobell et al., 2005) have found that N response varies from year to year within and between fields. In other words, potential yield and N requirements vary temporally and spatially within and between fields. This variability results from weather, topology, and their combined effects on N deposition, mineralization, and volatilization. Precision agriculture focuses on providing information to reduce uncertainty about N needs so producers can improve profit margins by avoiding under- or over-application of N.

Optical reflectance imaging (ORI) data gathered from plants during the growing season have been used to predict crop yields, and applications to precision agriculture have been developed (Clevers, 1997; Raun et al., 2002; Haboudane, 2002). Two technologies using this type of data are currently being extended to producers by agricultural engineers and agronomists of the Oklahoma Cooperative Extension Service. One technology, the Greenseeker system, makes an N needs prediction for plots as small as $1m^2$ (Raun et al., 2005a). The other is a whole field system that makes a uniform N requirement prediction for each entire field. Both systems predict the mid-season topdress N application rate at which the crop ceases to respond to additional N by use of either a *ramped* N strip (where N increases in 13 lb increments in plots along the length of the strip) or comparison of an N-*rich* strip (where N is not limiting) with an untreated, adjacent strip. Use of the N-rich strip requires an assumption of a constant marginal product of N across all fields, while the ramped strip allows this parameter to vary between fields. The Greenseeker system has been on the market for some time, but has faced slow adoption rates. Whole-field based technology provides less information, but may have a better chance of adoption due to its lower cost and lower need for specialized equipment. Though both systems require an experimental strip in each field to provide sensor data for predictive use, the field-based system has lower costs than the Greenseeker technology because it can use current N applicators.

A region-based system would have even lower costs, since it would only be necessary to put experimental strips on a few fields and then make the information publicly available through extension outlets. Regional data and predictions could be used by producers who graze wheat, for whom the cost of establishing and fencing an experimental strip is likely prohibitive. This article seeks to determine the potential profitability of regional versus single-field N needs prediction systems.

Our first objective is to determine whether year has an impact on regional crop N requirements. We also test for annual effects on ORI-based, mid-season predictions of N requirements. Ultimately, we calculate expected net returns for four different N application systems, including: 1) a naïve system applying only preplant anhydrous ammonia at 80 lb N ac^{-1}; 2) a naïve system applying only preplant UAN at 80 lb N ac^{-1};

3) an ORI-based system that predicts regional N requirements each year; and 5) an ORI-based system that predicts field-specific N requirements each year. We use paired differences tests to determine whether expected net returns from these application systems differ significantly. Sensitivity analysis is also conducted to determine how input and output prices affect the relative profitability of the four systems.

Theory

A crop producer's objective is to maximize expected net returns by the selection of N application rate under uncertainty about crop N requirements. The objective function is as follows:

$$
\begin{aligned}
&\max \pi(N) = \mathrm{E}[Y(N)]p_c - p_n N - \mathbf{r}'\mathbf{x} \\
&s.t. \quad N \geq 0 \\
&\qquad\ \ \mathbf{x} \geq 0
\end{aligned}
\tag{1}
$$

where $Y(N)$ is crop yield as a function of *N*—the N application rate; p_c is the price of the crop; p_n is the price of N; $\mathbf{r}$ is a vector of prices for inputs other than N, such as the cost of an experimental strip, and custom N application costs; and $\mathbf{x}$ is a vector of non-N input requirements. The producer's choice problem is complicated by variation of N needs over time and space. N requirements vary from year to year, from field to field, and even between plots in a single field.

Plant needs will in this way because the need for N fertilizer depends on an amalgamation of soil chemical and physical properties and climatological factors that vary across time, space, or both, affecting rates of N mineralization, deposition, and volatilization within and between fields and years (Mamo et al., 2003). Many studies support the use of functions derived from the von Liebig hypothesis to model agricultural production (e.g., Paris and Knapp, 1989; Berck and Helfand, 1990; Paris, 1992; Chambers and Lichtenberg, 1996; Berck, Geoghegan, and Stohs, 2000; Monod et al., 2002). In other words, prior research indicates that output is a function of the most limiting input. Here, the most limiting input is assumed to be either N or an unspecified input that is represented as a plateau level of output. Tembo et al. (2008) model to include both year and field effects, as well as allowing the slope to vary by field and year. Thus, crop N response over a given region is assumed to follow the form:

(2) $$Y_{pit} = \min(\beta_0 + \beta_{1it} N_{pit} + v_i + \varepsilon_t, P + v_i + \omega_i + \varepsilon_t + \upsilon_t) + u_{pit}$$

where Y_{pit} is the yield on plot *p* in field *i* in year *t*; N_{pit} is the N application rate on plot *p* of field *i* in year *t*; β_0 and P are the estimated intercept and yield plateau, respectively; β_{1it} is a slope parameter that is random by field-year[1], distributed normally with mean β_1 and variance $\sigma^2_{\beta_1}$; v_i and ω_i are random effects for field, shifting the intercept and plateau, respectively; ε_t and υ_t are random effects for year, also shifting the intercept and plateau; u_{pit} is a random disturbance from the mean; and v_i, ω_i, ε_t, υ_t, and u_{pit} are all independent and normally distributed with means of zero and variances σ^2_v, σ^2_ω, σ^2_ε, σ^2_υ, and σ^2_u, respectively. Thus, when the true parameters of equation (2) are known, the uniform rate profit maximizing N requirement for field *i* in year *t* (N_{it}) can be expressed as follows:

(3) $$N_{it} = \begin{cases} \mu + \omega'_i + \upsilon'_t, & \text{if } \beta_{1it} p_c \geq p_n \text{ and } (P + \omega_i + \upsilon_t - \beta_0) p_c - p_n(\mu + \omega'_i + \upsilon'_t) \geq p_a \\ 0, & \text{otherwise,} \end{cases}$$

[1] Allowing the slope to vary by field-year produces a model consistent with ramped strips.

where $\mu = (P - \beta_0) / \beta_{1it}$ is the mean N requirement for the region; $\omega'_i = \omega_i / \beta_{1it}$ is a random effect for field *i*; $\upsilon'_t = \upsilon_t / \beta_{1it}$ is a random effect for year *t*; and p_c, p_n, and p_a are the crop price, the price of N, and the N application cost, respectively. The condition $\beta_{1it} p_c \geq p_n$ requires that the value of the marginal product of N be greater than the price of N, while $(P + \omega_i + \upsilon_t - \beta_0) p_c - p_n(\mu + \omega'_i + \upsilon'_t) \geq p_a$ requires that increase in profit from N application be greater than the application cost. When all parameters are known with certainty, equation (3) can simply be plugged into equation (2) to calculate expected yield for field *i* in year *t*. However, when the parameters of (3) are estimated by equation (2), μ, ω'_i, and υ'_t are distributed as ratios of arbitrary, normally distributed random variables—a Cauchy-like distribution described by Marsaglia (1965). Because the estimated parameters of (2) and (3) are uncertain, and because of the form of the uncertainty, it is likely that simply plugging these expressions into equation (1) will not necessarily be optimal. However, determination of a more accurate formula for the optimal N rate through numerical intergration or Bayesian analysis is beyond the scope of this paper.

Due to variation in weather and soil properties over space, it is also reasonable to assume that the ω'_i exhibit spatial autocorrelation of the form:

(4) $$\boldsymbol{\omega}' = \rho \mathbf{W} \boldsymbol{\omega}' + \boldsymbol{\varepsilon}$$

where $\boldsymbol{\omega}'$ is a column vector of spatially autocorrelated error terms for all fields *i*, $i = 1, \ldots, N$; ρ is the spatial autocorrelation parameter; $\mathbf{W}$ is the square spatial weights matrix indicating the relative distances between all fields *i* and *j* ($i, j = 1, \ldots, N$); and $\boldsymbol{\varepsilon}$ is a vector of innovation terms for each field *i*, $i = 1, \ldots, N$, distributed iid normal.

Given this model of N needs, if $\sigma^2_{\omega'}$ is zero, the expected yield maximizing N application rate for the region in year *t* is:

$$N_{it} = \begin{cases} \mu + \upsilon'_t , & \text{if } \beta_{1it} p_c \geq p_n \text{ and } (P + \upsilon_t - \beta_0) p_c - p_n (\mu + \upsilon'_t) \geq p_a \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Regardless of the size of $\sigma^2_{\omega'}$, a large $\sigma^2_{\upsilon'}$ means that υ'_t explains a large part of variation in N requirements. Recall that $\upsilon'_t = \upsilon_t / \beta_{1it}$, so the annual effect on N requirements could be large either due to a large annual effect on the yield plateau or due to a small marginal product of N. While a field-based N requirement prediction system using ramped N strips accounts for ω'_i and υ'_t by placing an experimental strip in each field, a region-based system only accounts for υ'_t. For a field-based system to be more valuable than a region-based system, accounting for ω'_i—by placing an experimental strip in each field each year—must increase expected revenues more than it increases costs, as compared with accounting for υ'_t alone. Thus, assuming the υ'_t are predictable based on ORI data, a regional N requirement prediction system may provide valuable information for producers seeking to avoid monetary losses due to under- or over-application of N.

Data

Data for this research were collected from nine winter wheat fields throughout the state of Oklahoma. The nine fields are located at the Perkins, Stillwater, Efaw, Hennessey, Haskell, Tipton, Lahoma, and Lake Carl Blackwell agricultural experiment stations. In each field, N was applied on plots at varying rates with several replications at each rate between 1998 and 2006, though not all fields were sampled each year. The N application rate, in-season ORI measure, and yield were recorded for each plot. Observations are available at Perkins, with Teller sandy loam (fine-loamy, mixed, thermic Udic Argiustolls), from 1998 to 2006. At Stillwater, on Norge silt loam (fine-silty, mixed, thermic Udic Paleustolls), data were collected from 1999 to 2006. Experiments were conducted at Efaw on Easpur loam (fine-loamy, mixed superacitve thermic Fluventic Haplustolls) from 1999 to 2006. In 2000 and 2002, observations were collected at Hennessey on Shellabarger sandy loam (fine-loamy, mixed, thermic Udic Argiustolls). The field at Haskell has observations on Taloka silt loam (fine, mixed, thermic Mollic Albaqualfs) from 1999 to 2002. Data were collected on Lahoma's Grant silt loam (fine-silty, mixed, thermic Udic Argiustolls) from 1999 to 2006, with the exception of 2001. At the Tipton field, from Tipton silt loam (fine-loamy, mixed, thermic Pachic Argiustolls), data were collected only in 1998. Lake Carl Blackwell, with Port silt loam (fine-silty, mixed thermic Cumulic Haplustolls), produced observations in 2004 and 2005. The map in figure 1 shows the locations of the experimental fields.

Based on local cooperative prices, this paper assumes an N price of \$0.50 per pound from UAN 28-0-0, and an N price of \$0.28 per pound from anhydrous ammonia. Custom application costs for UAN and anhydrous (with knife application) are \$5.25 and \$6.00 per acre, respectively. We assume a wheat price of \$8.00 per bushel, and that the cost of creating an experimental strip is \$60. We also assume a field size of 40 acres, so the cost of an experimental strip is \$1.50 acre^{-1}.

Procedures

Testing for Annual Effects on N Requirements

Our first objective is to test whether annual effects on N requirements exist. Ideally, equation (2) would be used to test for these annual effects. However, equation (2) has five distinct random parameters— β_{1it}, v_i, ω_i, ε_t, and υ_t —depending upon field-year (*it*), field (*i*), and year (*t*). Restricting the slope to be constant across the region and estimating fixed effects (as opposed to random effects) for field allows the use of currently available statistical software. Furthermore, the small number and wide dispersion of fields available in our data set is not sufficient to estimate a spatial autocorrelation coefficient. Therefore, we estimate the following model:

$$(6) \qquad Y_{pit} = \min(\beta_0 + \beta_1 N_{pit} + v_i + \varepsilon_t, P + v_i + \omega_i + \varepsilon_t + \upsilon_t) + u_{pit}$$

where Y_{pit} is yield on plot *p* of field *i* in year *t*; β_0 is the intercept; β_1 is the slope, and is restricted to be the same for all fields and years[2]; v_i and ω_i are fixed effects for field *i*, shifting the intercept and plateau, respectively; F_i is a indicator variable for field *i*; ε_t and υ_t are random effects for year *t*, shifting the intercept and plateau, respectively; u_{pit} is an error term; and ε_t, υ_t, and u_{pit} are distributed independently with means of zero and variances σ_ε^2, σ_υ^2, and σ_u^2, respectively. Equation (5) is our unrestricted model because it allows the plateau to be random not only by field but also by year (i.e., σ_υ^2 is estimated). The null hypothesis is that year does not affect N requirements, or $\sigma_\upsilon^2 = 0$. We test the restriction that annual effects on N requirements do not exist by estimating a model based on equation (5), imposing the single restriction that σ_υ^2 —the plateau random effect for year—is zero. Thus, the likelihood ratio statistic to test for the existence of annual effects on N requirements is distributed chi-square with one degree of freedom. Rejection of the null hypothesis would indicate that year affects N requirements.

[2] Note that restricting the slope to be constant across all fields produces a model representative of the N-rich strip method, whereas equation (1) is more closely aligned with the ramped strip method.

Testing for Annual Effects on ORI-based N Requirement Predictions

The next question is whether year also affects on ORI-based *predictions* of N requirements. We therefore reestimate the unrestricted and restricted models based on (5), replacing yield with the ORI measure as the dependent variable, and again conduct the likelihood ratio test. Rejection of the null hypothesis in this case would indicate that, if annual effects on N requirements exist, they *may* be predictable using ORI data.

Net Revenue for a Naïve System using Preplant UAN or Anhydrous Ammonia

We begin to establish the value of increasingly precise spatial information by estimating expected profit from a naïve, non-precise application decision, where N is applied at 80 lb ac^{-1} prior to planting as UAN, regardless of field or year. To do so, we first estimate a unique production function for each field-year (i.e., for each field in each year). These functions are estimated as follows:

(7) $$Y_{pit} = \min(\beta_{0it} + \beta_{1it} N_{pit}, P_{it}) + u_{pit}$$

where Y_{pit} is yield on plot *p* in field *i* in year *t*, β_{0it} is the yield intercept for field *i* in year *t*, β_{1it} is the crop N response in field-year *it*[3], N_{pit} is the N application rate on plot *p* in field *i* in year *t*, P_{it} is the yield plateau for field *i* in year *t*, and u_{pit} is a normally distributed error term specific to field *i* in year *t* with mean zero and variance σ_u^2. By plugging the naïve recommendation of 80 lb N ac^{-1} into each field-year's estimated production function from (7), we calculate each field-year's expected yield. The expected yield and the N application rate of 80 lb ac^{-1} are then plugged into the producer's

[3] Note that allowing the slope to vary by field-year is consistent with the ramped N strip method. Here, we are able to do this because we estimate the production function for each field-year individually.

objective function in (1) to find the expected net revenue for each field-year. In the case of the naïve system, $\mathbf{r}'\mathbf{x}$ always includes p_a—the cost of N application. We calculate expected net revenue for each field year using both UAN and anhydrous ammonia.

Net Revenue for a Field-based System Using Only Topdress UAN

Currently, the field-based system predicts the optimal N application rate for each field-year by estimating a regression of ORI measures on N application rates in ramped strip plots as follows:

$$(8) \qquad Y_{pit}^{P} = \min(\beta_{0it}^{P} + \beta_{1it}^{P} N_{pit}, P_{it}^{P}) + u_{pit}^{P}$$

where Y_{pit}^{P} is the ORI measure on plot *p* in field-year *it*, β_{0it}^{P} is the intercept of ORI in field-year *it*, β_{1it}^{P} is the N response of ORI in field-year *it*, N_{pit} is the N application rate on plot *p* in field-year *it*, P_{it}^{P} is the plateau of ORI measures in field-year *it*, and u_{pit}^{P} is a normally distributed error term specific to field-year *it* with mean zero and variance $\sigma_{u^P}^2$. In effect, the field-specific ramped strip system estimates fixed effects for field-year, rather than separate random effects for field and year, as in equation (2). The predicted yield maximizing N application rate for each field-year is approximated as:

$$(9) \qquad N_{it}^{YP} = \frac{P_{it}^{P} - \beta_{0it}^{P}}{\beta_{1it}^{P}}.$$

However, at times it is not profitable to apply N, as is the case the price of N exceeds the value of the marginal product of N. The predicted net revenue maximizing N rate for each field-year is then calculated as:

$$(10) \qquad N_{it}^{\pi P} = \begin{cases} N_{it}^{YP}, & \text{if } \beta_{1it}^{P} p_w > p_n \text{ and } p_w(P_{it}^{P} - \beta_{0it}^{P}) - p_n N_{it}^{YP} > p_a \\ 0, & \text{otherwise.} \end{cases}$$

Expected yield is calculated for each field-year by plugging the field-specific ORI-based N application rate from (10) into equation (7). These expected yields are used in the objective function in equation (1) to calculate expected net revenue. In the case of this field-based system, $\mathbf{r'x}$ always includes the cost of a ramped strip, but only includes application costs if the predicted profit maximizing application rate is greater than zero.

Net Revenue for a Region-based System Using Only Topdress UAN

The proposed region-based system predicts N requirements for the entire region by treating ramped strips at several experiment stations and other locations within the region as one large ramped strip, and annually estimating the function:

$$Y_{pt}^{R} = \min(\beta_{0t}^{R} + \beta_{1t}^{R} N_{pt}, P_{t}^{R}) + u_{pt}^{R} \tag{11}$$

where Y_{pt}^{R} is the ORI measure on plot *p* in year *t*; β_{0t}^{R} is the intercept for year *t*; β_{1t}^{R} is the slope in year *t*; N_{pt} is the N application rate on plot *p* in year *t*; P_{t}^{R} is the plateau in year *t*; and u_{pt}^{R} is an error term distributed normal with mean zero and variance $\sigma_{u^R}^{2}$. We simulate a regional prediction for each field-year by using all other fields available in the same year to estimate equation (11). This process attenuates in-sample bias and simulates a region-based prediction by using only the regional information from other fields to predict the optimal rate for each field. The predicted optimal region-based N application rate for field *i* in year *t* is then calculated as:

$$N_{it}^{R} = \begin{cases} N_{it}^{YR}, & \text{if } \beta_{1t}^{R} > p_n \text{ and } p_c(P_t^R - \beta_{0t}^{R}) - p_n N_{it}^{YR} > p_a \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

where $N_{it}^{YR} = (P_t^R - \beta_{0t}^{R}) / \beta_{1t}^{R}$ is the regional yield maximizing application rate. Because the parameters estimated in (11) and used in (12) use data from several different fields, these estimates include not only within field variation but also between field variation. Ultimately, this means that the predictions from the region-based system are less precise than those of the field-based system. Still, plugging these predictions into the field-year production functions from (7) provides consistent estimates of expected yield by the Slutsky Theorem. We then calculate expected net return for each field-year by plugging the expected yield and the optimal N application rate from (12) into the objective function in equation (1). For the region-based system, $\mathbf{r'x}$ does not include the cost of an experimental strip, and only includes application cost if N_{it}^{R} is greater than zero

Differences in Expected Profit

After calculating net revenue for each field-year using the naïve system and the field-and region-based predictions, we conduct two paired differences tests—first on the paired differences between expected net revenue from the field-based system and expected net revenue from the region-based system, and then on the paired differences between expected net revenue from the region-based system and expected net revenue from the naïve system. The statistic the paired differences test is test is:

(13)
$$T = \frac{\left(\sum_{it=1}^{n}[E(\pi_{it}^{0}) - E(\pi_{it}^{A})]\right)\Big/ n}{\hat{\sigma}\big/\sqrt{n}} \sim t_{n-1}$$

where π_{it}^{0} is profit for field-year *it* using one application system; π_{it}^{A} is profit from for field-year *it* using another system; *n* is the total number of field-years; and $\hat{\sigma}$ is the sample standard deviation of the paired differences. A two-tailed *t*-test is performed to test the null hypothesis that there is no mean difference in net revenue between the field-based and region-based systems. Next, we use a *t*-test to test the null hypothesis that there is no difference in net revenue between the regional system and the naïve system (80 lb N ac^{-1} from UAN). We also calculate the difference between using 80 lb N ac^{-1} from preplant UAN and using 80 lb N ac^{-1} from anhydrous ammonia. A paired differences test is unnecessary in this case, as the expected profit difference between naïve UAN application and naïve anhydrous ammonia application at 80 lb N ac^{-1} is constant. We conduct sensitivity analysis to determine the effects of high N prices and low wheat price.

Results

We find that annual effects on N requirements are statistically significant, as are annual effects on ORI-based N requirements predictions. The first column of results in table 1 presents the unrestricted model from equation (5)—i.e., with random annual effects on the plateau—using yield as the dependent variable, while the second column exhibits restricted model, which assumes σ_{υ}^{2} is zero. The likelihood ratio statistic is 40.40, while the critical value at the 0.01 level is 6.635. Therefore, we reject the null hypothesis of no annual effects on N requirements. The third and fourth columns, respectively, show estimation results for the same unrestricted and restricted models, but using ORI measures as the dependent variable. The results in these columns are used to test the null hypothesis that year has no effect on N requirement predictions. The likelihood ratio statistic is 29.80, so we again reject the null hypothesis, and conclude that year affects ORI-based N requirement predictions.

Given current N and wheat prices and application costs, the average field-based system N recommendation is 63 lb ac^{-1}, and the region-based system recommends 61 lb ac^{-1} for the average field-year. Average net returns above N purchase, N application, and experimental strip creation using the field-based system are \$307.20 ac^{-1}, compared with

$302.48 ac^{-1} for the regional system and $318.46 ac^{-1} for preplant UAN at 80 lb N ac^{-1}. Application of 80 lb N ac^{-1} from anhydrous ammonia is clearly the most profitable, with a net return of $335.31 ac^{-1}. The average paired difference between net revenues using the field-based system and net revenues using the regional system is $4.71 ac-1; however, the null hypothesis that there is no revenue difference between the two systems cannot be rejected because the *t*-value for this paired difference test is 0.46, while the *t*-critical value with 41 degrees of freedom at the 0.1 level is 1.683. The mean of the paired revenue differences from the region-based system and those of the naïve system applying 80 lb N ac^{-1} from preplant UAN is -$15.97, meaning that the naïve system provides greater profits than the region-based system by $15.97 ac^{-1}. This difference is significantly different from zero, as the *t*-statistic for the test is 2.46 and the *t*-critical value is 2.02 at the 0.05 level. The naïve system using anhydrous ammonia is $16.85 ac^{-1} more profitable than the naïve system using UAN.

Next, while holding the price of wheat constant at $8 bu^{-1}, we consider the effect of increasing the price of N from UAN to $1.50 lb^{-1} and the price of anhydrous ammonia to $0.84 lb^{-1}. Under this scenario, the average field-based recommendation is 20 lb ac^{-1}, while the average region-based recommendation is 37 lb ac^{-1}. The expected profit difference between field-based and region-based recommendations is $28.19 ac-1, and is statistically significant and is strongly significant (p = 0.0004). The regional system, however, is not statistically superior to naïve application of UAN (p = 0.915), since the return to the regional ORI information is only $1.15 ac^{-1} on average.

While holding N prices constant at $0.50 lb^{-1} and $0.28 lb^{-1} for UAN and anhydrous ammonia, respectively, we also consider a scenario in which wheat price is $3.00. Here, average application rates from the field-based and regional systems are 25 and 43 lb ac^{-1}, respectively. The field-based system is more profitable than the regional system by \$6.22 ac^{-1}, but this number is not statistically significant ($p = 0.11$). The expected profit difference between the regional and naïve preplant UAN approach continues to be small (\$1.42) and insignificant ($p = 0.663$). Of course, naïve preplant application of anhydrous ammonia prior to planting is the most profitable of all the application systems considered here under the above price scenarios, though this advantage decreases with the price of wheat.

Conclusions

Our results show that annual effects on crop N requirements exist, and may be predictable based on ORI data. However, the proposed regional N topdress recommendation system, which attempts to account for these annual effects, shows no clear and consistent advantage over the naïve systems applying either UAN or anhydrous ammonia at 80 lb N ac^{-1}. This result likely stems partially from the lack of uniformity in climate and soil physical and chemical properties among the experiment station locations used in this study. Even at the sites located in Payne County alone (Efaw, Stillwater, Perkins, and Lake Carl Blackwell), soil types include various types of fine loamy and fine silty soils. Because of the wide variability in the study region, this research likely underestimates the value of the currently proposed regional recommendation system. Some areas of the state of Oklahoma are less variable in soil-type and climate, as is the case in western Oklahoma, where the region to which a prediction could apply might be very large, as climate and soil types vary less over space. In these areas, the regional regression approach might be more viable, though not exactly optimal due to uncertainty about the regression parameters.

However, a regional system could be developed to serve a large number of producers across a widely variable region. Optimal N recommendations under uncertainty might be obtained from a Bayesian framework using numerical integration in conjunction with the regional regression results and prior, historical information about a given field. Since producers generally keep track of historical information on N application and yield for their fields, this prior information will often be available. Thus, prior to implementing a region-based system for N recommendation the system as currently proposed will have to be updated to truly optimize profits.

In short, our results indicate that under some input and output price scenarios, the currently proposed regional system is just as profitable as the naïve system of 80 lb ac^{-1} from UAN, and that the regional system reduces the average N application rate for the entire region. Thus, the regional recommendation system provides benefits in the form of reduce N runoff from agricultural production.

The reality is, however, that most producers use split N applications, applying substantial N prior to planting as anhydrous ammonia, and apply topdress UAN mid-season only if the crop looks good or if the crop produced plenty of forage for grazing. A region-based annual N recommendation—whether based solely on the regional regression approach or on a Bayesian framework—will be most valuable to producers who were unable to apply preplant anhydrous ammonia due to excessively wet or dry weather, for producers who did not apply enough preplant anhydrous, and for those cannot establish their own experimental strips due to grazing.

References

Berck, P., J. Geoghegan, and S. Stohs. 2000. “A Strong Test of the von Liebig Hypothesis.” *American Journal of Agricultural Economics* 84(4):948-955.

Berck, P., and G. Helfand. 1990. “Reconciling the von Liebig Hypothesis and Differentiable Crop Production Functions.” *American Journal of Agricultural Economics* 84(4): 985-96.

Cassman, K.G., S. Peng, D.C. Olk, J.K. Ladha, W. Reichardt, A. Doberman, and U. Singh. 1998. “Opportunities for Increased Nitrogen-Use Efficiency from Improved Resource Management in Irrigated Rice Systems.” *Field Crops Research* 56(1-2): 7-39.

Chambers, R.G., and E. Lichtenberg. 1996. “A Nonparametric Approach to the von Liebig-Paris Technology.” *American Journal of Agricultural Economics* 78(2): 373-386.

Clevers, J.G.P.W. 1997. “A Simplified Approach for Yield Prediction of Sugar Beet Based on Optical Remote Sensing Data.” *Remote Sensing of Environment* 61(2): 221-228.

Greenhalgh, S., and P. Faeth. 2001. “A Potential Integrated Water Quality Strategy for the Mississippi River Basin and the Gulf of Mexico.” *The Scientific World* 1: 976-983.

Haboudane, D., J.R. Millera, N. Tremblayc, P.J. Zarco-Tejadad, L. Dextrazec. 2002. “Integrated Narrow-Band Vegetation Indices for Prediction of Crop Chlorophyll Content for Application to Precision Agriculture.” *Remote Sensing of Environment* 81(2): 416-426.

Lobell, D.B., J.I. Ortiz-Monasterio, G.P. Asner, R.L. Naylor, and W.P. Falcon. 2005. "Combining Field Surveys, Remote Sensing, and Regression Trees to Understand Yield Variations in an Irrigated Wheat Landscape." *Agronomy Journal* 97(1): 241-249.

Mamo, M., G.L. Malzer, D.J. Mulla, D.R. Huggins, and J. Strock. 2003. "Spatial and Temporal Variation in Economically Optimum Nitrogen Rate for Corn." *Agronomy Journal* 95(4): 958-964.

Marsaglia, G. 1965. "Ratios of Normal Variables and Ratios of Sums of Uniform Variables." *Journal of the American Statistical Association* 60 (309): 193-204.

Monod, H., D. Makowski, M. Sahmoudi, and D. Wallach. 2002. "Optimal Experimantal Designs for Estimating Model Parameters, Applied to Yield Response to Nitrogen Models." *Agronomie* 22: 229-238.

Paris, Q. 1992. "The von Liebig Hypothesis." *American Journal of Agricultural Economics* 74(4): 1019-1028.

Paris, Q., and K. Knapp. 1989. "Estimation of von Liebig Response Functions." *American Journal of Agricultural Economics* 71(1): 178-186.

Raun, W.R., and G.V. Johnson.1999. "Review and Interpretation: Improving Nitrogen Use Efficiency for Cereal Production." *Agronomy Journal* 91(3): 357-363.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, R.W. Mullen, K.W. Freeman, W.E. Thomason, and E.V. Lukina. 2002. "Improving Nitrogen Use Efficiency in Cereal Grain Production with Optical Sensing and Variable Rate Application." *Agronomy Journal* 94(2): 815-820.

Raun, W.R, J. B. Solie, M. L. Stone, D. L. Zavodny, K. L. Martin, and K. W. Freeman. 2005a. "Automated Calibration Stamp Technology for Improved In-Season Nitrogen Fertilization." *Agronomy Journal* 97(1): 338-342.

Raun W.R., J.B. Solie, M.L. Stone, K.L. Martin, K.W. Freeman, R.W. Mullen, H. Zhang, J.S. Schepers, and G.V. Johnson. 2005b. "Optical Sensor-Based Algorithm for Crop Nitrogen Fertilization." *Communications in Soil Science and Plant Analysis* 36(19-20): 2759-2781.

Tembo, G., B.W. Brorsen, F.M. Epplin. 2008. "Linear Response Stochastic Plateau Functions." *American Journal of Agricultural Economics*, Forthcoming.

United States Department of Agriculture. 2005. "Commodity Costs and Returns: The Economics of Food, Farming, Natural Resources, and Rural America." Economic Research Service. Available at: http://www.ers.usda.gov/Data/costsandreturns/testpick.htm.

Washmon, C.N., J.B. Solie, W.R. Raun, and D.D. Itenfisu. 2002. "Within Field Variability in Wheat Grain Yields over Nine Years in Oklahoma." *Journal of Plant Nutrition* 25(12): 2655-2662.

Table 1. Restricted and Unrestricted Stochastic Plateau Models for Optical Reflectance and Yield Data Sets

Parameter	Description	Yield Data		Optical Reflectance Data	
		Unrestricted Model[a]	Restricted Model[b]	Unrestricted Model[a]	Restricted Model[b]
P	PlateauYield	44.409*** (1.564)	44.858*** (3.238)	45.128*** (3.443)	46.156***[c] (2.244)
β_0	Intercept	39.161*** (2.333)	32.522*** (3.946)	34.624*** (2.790)	32.632*** (2.302)
β_1	Slope	0.240*** (0.085)	0.273*** (0.037)	0.214*** (0.017)	0.213*** (0.021)
σ_u^2	Error term	123.510*** (7.639)	138.830*** (8.593)	58.466*** (3.594)	65.433*** (4.058)
σ_v^2	Variance of field intercept fixed effects	66.784 (34.170)	94.487** (37.596)	4.725 (4.717)	15.436 (8.380)
σ_ω^2	Variance of field plateau fixed effects	399.220** (106.47)	115.540* (52.044)	82.445* (37.452)	6.502 (7.250)
σ_ε^2	Variance of annual intercept random effects	41.996*** (6.299)	57.732 (31.876)	38.004 (21.406)	24.328 (13.466)
σ_υ^2	Variance of annual plateau random effects	48.290*** (8.020)	-	35.112 (20.958)	-
Log-Likelihood Value		-2047.450	-2067.650	-1846.35	-1861.25

[a] The random year effect on the plateau is estimated.
[b] The random year effect on the plateau is assumed to be zero.
[c] Three, two and one asterisks (*) represent statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

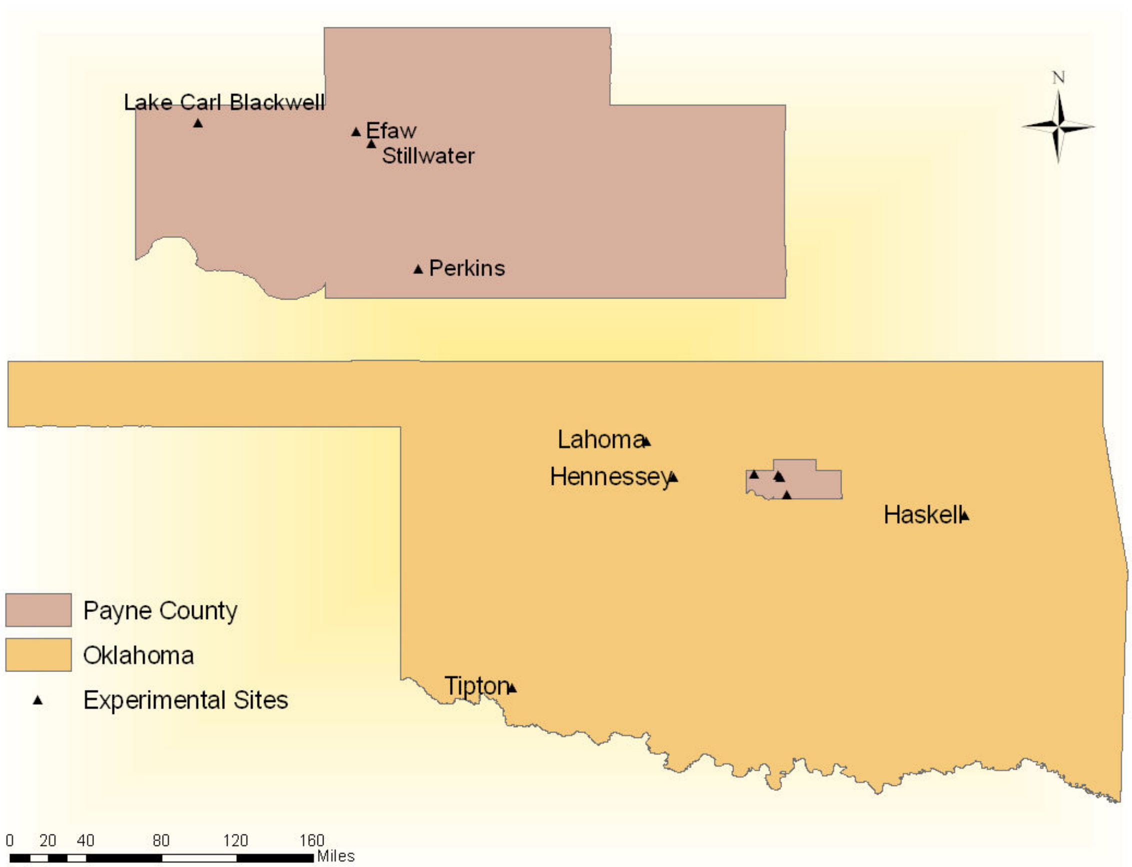

Figure 1. Locations of experimental sites