Comparing Profitability of Variable Rate Nitrogen Prescriptions

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Abstract.

Fertilization is crucial in cereal grain production, with nitrogen being a key yet volatile nutrient. Precision agriculture allows for tailored nitrogen recommendations using detailed spatial and temporal data. Most profitability studies of variable rate nitrogen (VRN) fertilization compare it to uniform rates, but the cost of data is a concern. With the increasing availability of data sources for VRN recommendations, it is important to assess the profitability of these information sources.

This study evaluates the ex post profitability of VRN prescriptions derived from different information sources. Using data from 10 Midwest fields in 2021, we compare nitrogen prescriptions using remotely sensed data to those using yield history. A quasi-experimental design is used to address non-random treatment assignment.

Preliminary findings show significant variability in prescription effectiveness across fields. Yield history-based prescriptions resulted in statistically higher gross margins on 1 of 7 fields (57%), while NDVI-based prescriptions did so on 1 of 7 fields (14%).

Keywords.
variable rate nitrogen; prescription profitability; quasi-experiment; fertilizer rate

Introduction

In agriculture, decisions hinge on real-time updates about dynamic environmental conditions, crop status, and crucially, crop prices and input costs. Among the many important tactical decisions that farmers face, fertilization holds significant importance, as it represents a major production cost for cereal grain crops. Particularly regarding nitrogen fertilizers, numerous factors come into play, as nitrogen is a volatile nutrient prone to loss from the root zone and the extent of nitrogen loss can vary depending on soil type and weather conditions.

In the past, nitrogen fertilizer recommendations relied on the concept of yield potential, representing the anticipated yield attainable by farmers under ideal conditions. Calculations for yield-maximizing nitrogen rates were straightforward, involving the multiplication of yield potential by a fixed parameter. However, these recommendations were primarily based on the average yield of a field, overlooking within-field variability. Furthermore, they remained static over time, as the underlying information used to formulate recommendations seldom changed. While variable rate nitrogen prescription based on grid soil testing attempted to address within-field variability, past research has highlighted various technical and economic limitations associated with this approach, which requires many costly soil test samples (Whelan et al., 1996; Fleming et al., 2000).

The spread of information technology has made obtaining quantitative information about fields, crops, and the environment more accessible, providing a wealth of data to guide fertilizer recommendations. This technological advancement enables us to develop nitrogen recommendations using detailed data at fine spatial and temporal resolutions, down to the sub-field level. By applying tailored nitrogen rates that align with the spatial variability and crop requirements within a field, variable rate nitrogen (VRN) application can enhance crop productivity, improve nitrogen use efficiency, and ultimately increase profitability for farmers.

A diverse array of information sources is now available for this purpose. For instance, current season crop growth information such as normalized difference vegetation index (NDVI) or chlorophyll index (CI), both based on data collected remotely using sensors, offers real-time insights for fertilization (Holland and Schepers, 2010; Jin et al., 2017; Solie et al., 2012). By contrast, yield maps enable the analysis of within-field yield variability across multiple years (Khakbazan et al., 2021; Laboski et al., 2012; Paz et al., 1999). These new types of information enable VRN prescriptions that are conditioned upon just-in-time weather and historic variability in ways that were heretofore impossible.

However, information costs money. Thus far, there is a dearth of comparative studies evaluating the returns to different types of information available to develop nitrogen fertilizer recommendations. Various nitrogen prescription methods have been suggested, but there is no consensus on which prescription algorithm and which information set is the most profitable. Each type of information can contribute to raising yields, reducing excessive inputs, or doing both simultaneously. How well they accomplish these goals may vary across different types of information. The cost of acquiring information is not always aligned with its effectiveness, and costs can vary greatly across information sources. Understanding the payoff associated with each type of information is a key step toward evaluating the cost effectiveness of information investments. As highlighted by Schimmelpfennig (2016), farmers who adopt site-specific technology allocate approximately 32% more of their budget to machinery investments compared to those who do not and returns to those investments are driven by information.

This study contributes to the existing literature on the profitability of variable-rate nitrogen application and the value of agricultural information. While numerous studies have investigated how different nitrogen prescription methods effectively increase crop yield compared to uniform rate application (Park et al., 2024; Khakbazan et al., 2021; Khanna, 2001; Babcock and Pautsch, 1998), little attention has been paid to determining which prescription method is the most profitable.

Studies comparing prescription methods based on different sources of information are limited, and there is no consensus on which information source most effectively increases farm profit. Among studies that have compared nitrogen prescriptions based on different sources of information, a common approach is to estimate the yield response function to nitrogen and assess how well agricultural information explains the optimal nitrogen rate (Hurley et al., 2001; Schmidt et al., 2011). This method has the advantage that it does not require prescriptions to be made from the information, and fields do not need to be treated with different prescriptions. However, this method requires a long span of data to validate the yield response function. Alternatively, by assigning different prescriptions, the treatment effect of prescribing nitrogen from each information source can be estimated (Stefanini et al., 2019). Schimmelpfennig and Ebel (2016) utilized survey data and found that soil maps contribute to production cost savings, but they did not consider the possible revenue change from yield change.

In this paper, we examine the *ex post* profitability of nitrogen prescriptions based on different sources of information. Using yield maps and nitrogen prescriptions from 10 fields in the Midwest in 2021, we compare a prescription based on remotely sensed data to a prescription based on yield history. Since the treatments were not randomly assigned, we employ a quasi-experimental design to disentangle the effects of the two different treatments derived from two different sources of information. After comparing the profitability of various information sources, we delve deeper into understanding the factors that contribute to the effectiveness of nitrogen prescription.

Data

We evaluate nitrogen fertilizer recommendations using corn yield data from ten fields located on two farms in Michigan and one in Indiana in 2021. Each field was divided into a grid, where the width of each cell was set equal to the width of the fertilizer applicator. Each grid cell serves as an observation unit for this analysis, with a total of 4,945 samples examined.

The nitrogen rate was varied solely for the second side-dress nitrogen application. Nitrogen fertilizers are typically applied to corn at multiple times during the year, including prior to planting, at planting, and one or more times at side-dress when the crop is growing. In this on-farm experiment, the participating farmers maintained uniform nitrogen rates for preplant and first side-dress applications but adjusted the nitrogen rate for the second side-dress application based on the given prescription.

The gross margin calculations use 2021 USDA corn prices from two states: Michigan corn grain price of \$5.35/bu and Indiana corn grain price of \$5.43/bu (USDA, 2023a; 2023b). The nitrogen fertilizer price of \$0.57/lb is from the USDA Agricultural Marketing Service Illinois Production Cost Report (USDA, 2022). As the side-dress nitrogen is applied in the form of 28% liquid nitrogen fertilizer, we calculate the price of nitrogen by dividing the liquid nitrogen price by 0.28, under the assumption that 28% of the liquid nitrogen price corresponds to the nitrogen content.

We use daily weather data at a resolution of 800m from Parameter-elevation Relationships on Independent Slopes Model (PRISM) to construct variables for growing degree days[1] (GDD), total precipitation, and number of days with maximum temperature below 15℃ for the duration of the growing season, spanning from April to September.

Descriptive statistics of the data used in the analysis are presented in Table 1. For the entire sample, the average corn yield is 190 bu/ac and the average gross margin from corn over the cost of the second side-dress nitrogen application is 996 \$/ac.

[1] $GDD = \sum Max(Avg.Temp - 10℃, 0)$

Table 1 Descriptive statistics for key variable rate nitrogen profitability variables, 10 corn fields, Michigan and Indiana, 2021 (n=4,945).

Variable	Average (Std. Dev.)	Min	Max
Gross margin ($/ac)	996 (260)	27.52	1433.08
Yield (bu/ac)	190 (50)	5.14	275.74
N rate (lb/ac)	42.56 (34.01)	0	106.90
NDVI level (Low=1, Med=2, High=3)	2.20 (0.70)	1	3
YH level (Low=1, Med=2, High=3)	1.89 (0.54)	1	3
Growing degree days (Apr-Sep)	1583 (71)	1509	1706
Total precipitation (Apr-Sep)	637 (56)	578	737
Max temp below 15℃ days (Apr-Sep)	40 (0.96)	38	43

Nitrogen prescriptions

Each farmer provided their historical yield map and nitrogen application map. The YH recommendation algorithm was based on yield history data. Remote sensing imagery (transformed into the Normalized Differential Vegetation Index; NDVI) constituted the data set for the NDVI recommendation algorithm and was collected before the second side-dressing. Both the historical yield (YH) map and the remote sensing imagery (NDVI) were classified into three levels: high, medium, and low, using Iso Unsupervised Classification in ArcGIS.

Then, both YH and the NDVI were integrated into the SALUS crop growth model (Basso et al., 2006) together to generate a nitrogen prescription for each field. Three nitrogen fertilizer levels (high, medium, low) were prescribed for each field as described in Basso et al., (2011, 2016). The specific rate of nitrogen at each level varies by field.

From the SALUS model, a single set of recommendations was generated, which, depending on instances, aligned with either a reliance on NDVI or YH. The prescribed nitrogen level aligned with the NDVI level when there is small discrepancy between NDVI and YH levels. Conversely, the prescription is aligned with the YH level in cases when 1) the NDVI level is high but YH is low, 2) the NDVI level is medium but YH is low with large historical variation, and 3) the NDVI is low but YH is medium with small variation across time. A full description of the nitrogen prescription algorithm for each possible combinations of NDVI and YH levels appears in Appendix.

Methods

In order to statistically estimate an unbiased treatment effect (e.g., from different information sets), the treatment assignment must either be randomized or exhibit enough variation to establish conditional independence of treatment assignment. However, in the current dataset, only one prescription has been applied to all observations, making it impossible to ensure the necessary variation. To overcome this challenge, we propose a quasi-experiment leveraging the unique characteristic of the prescription algorithm, which utilizes two sets of information, NDVI and YH together.

Creation of pseudo-treatment variables

As all the nitrogen prescriptions given to farmers are based on the combination of NDVI and YH, we generate treatment variables for the NDVI and YH methods by classifying each cell according to the nitrogen rate it received. For each treatment, we create a variable equal to 1 if the rate is prescribed following that information. For example, if the cell received the high nitrogen rate and its NDVI level is also high, the value of the NDVI treatment variable for that cell is 1. However, if the cell received the low nitrogen rate and its YH is low, but its NDVI level is high, the value of the NDVI treatment variable for that cell is 0 while the value of the YH treatment variable is 1.

Figure 2 describes two examples of how the pseudo-treatment variables are generated. Cell A, which has high NDVI and medium YH, received the high nitrogen rate. So, its NDVI treatment variable is 1 because its nitrogen recommendation is consistent with NDVI information, whereas its YH treatment variable is 0 because YH alone would not have given a high nitrogen recommendation. On the other hand, Cell B received the medium nitrogen rate, and both of its NDVI and YH levels are medium. Therefore, the NDVI and YH treatment variables are both 1.

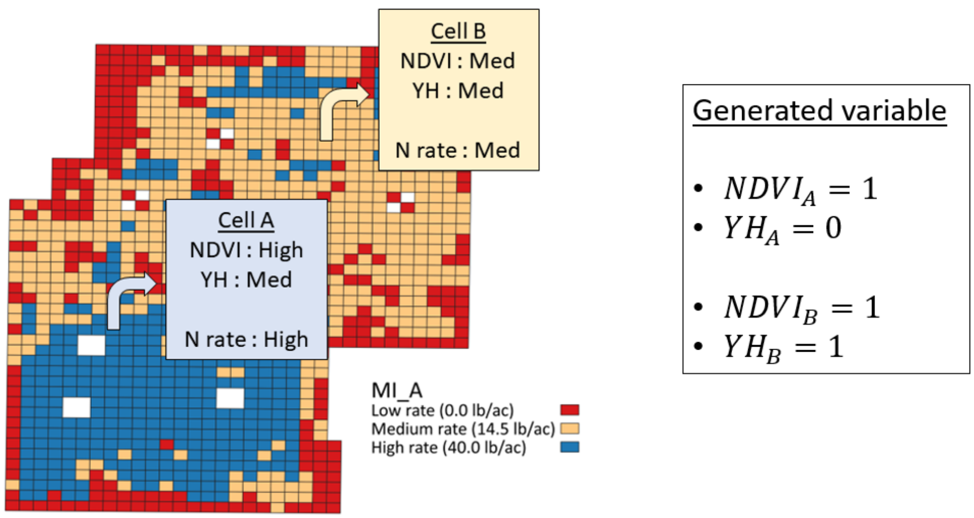

Figure 1 Example of pseudo-treatment variable

Estimation strategies

Although we can generate pseudo-treatment variables, their non-random assignment calls for further consideration. We propose two estimation strategies: linear regression and spatial regression discontinuity. Given that the gross margin is closely related to applied nitrogen rate, site characteristics, and weather conditions, the proposed estimation strategies control for the effects other than the choice of information utilized for prescription and allows us to examine the treatment effect while holding all other factors equal. Linear regression incorporates covariates to capture non-treatment effects on gross margin, while spatial discontinuity design leverages the fact that contiguous samples can be assumed to have similar characteristics.

Linear regression

Assuming that the relationship between the gross margin and the treatment variables is linear, we can estimate the effect of each treatment by linear regression. The profitability of each treatment is estimated with the following equation.

$$\pi_{it} = \sum_{t}(\beta_{0t} + \beta_{1t}NDVI_i + \beta_{2t}YH_i) * YEAR_t + \gamma_1 Site\ charact_i + \gamma_2 Weather_{it} + \gamma_3 Field_i$$

(5)

The dependent variable is the gross margin of corn revenue minus the cost of nitrogen fertilizer. $NDVI_i$ and YH_i indicate the NDVI treatment and YH treatment respectively. The effects of prescription methods are interacted with year indicator variable ($YEAR_t$), representing the differential impact of the prescription methods contingent on the weather patterns of each year. Because our data includes only the year 2021, we omit the interaction with year in the estimation regression. Site $charact_i$ is a vector of all variables that are specific to each cell, such as slope, NDVI and YH level. $Weather_{it}$ is a vector of weather conditions specific to cell and year that is comprised of growing degree days and total precipitation during the growing season. $Field_i$ represents a vector of field fixed effect controlling for all the field specific effect such as farmer, previously planted crop, and location. The effect of the NDVI treatment and YH treatment are represented by the coefficients β_1 and β_2 respectively in Equation (5).

This method is characterized by its ease of implementation, its capacity to control variables that may be correlated with the gross margin, and its facilitation of statistical inference. Also, despite the simplicity of estimation, it does not show any statistical differences from Bayesian regression or random forest regression (Paccioretti et al., 2021). Nonetheless, because treatments were not randomly assigned, the estimated treatment effect may be biased. The nitrogen prescription algorithm applied in this experiment tends to choose the NDVI treatment when the NDVI level is high, so the NDVI method is more likely to be assigned to a cell with higher level of YH, whereas the YH method is more likely to be assigned to a cell with lower level of NDVI. When we compare the mean of NDVI and YH level of two groups in Table 2, one group treated with the NDVI method and one treated with the YH method, the results of the unpaired t-test suggest that the NDVI and YH variables of the two methods are statistically distinguishable at a significance level of less than 1%.

Table 2 Mean values of key variables, by information treatment

	Treated with NDVI (n=4,204)	Treated with YH (n=3,194)
Gross margin ($/ac)	1018	984
Yield (bu/ac)	194	187
N rate (lb/ac)	46.16	36.85
NDVI level	2.24	1.95
YH level	1.97	1.83

Spatial discontinuity design

This method compares the gross margin response of two adjacent grid cells under the assumption that all site characteristics, including YH and NDVI, are virtually identical except for the information used to make the nitrogen prescription. Specifically, we focus on comparing pairs of cells that received the same nitrogen rate. By doing so, we isolate the impact of information choice on gross margin, as any difference observed between adjacent cells with different information choices can be attributed to the information used for nitrogen prescription.

This approach bears resemblance to the spatial regression discontinuity design, which also involves the consideration of spatial factors. However, we cannot classify this method as the spatial regression discontinuity design because the spatial factor alone in this approach does not dictate the treatment assignment. Rather, the spatial component is only used as the basis for assuming similarity between two adjacent cells.

We consider “rook” neighbors, which include only grid cells that share a side. Cell *i* is defined as a YH treated unit and cell *j* is defined as an NDVI treated unit if the following conditions are met:

1) they have received the same nitrogen rate, 2) cell i is prescribed following YH level, 3) cell j is prescribed following NDVI level, and 4) the YH and NDVI levels of cells i and j do not match. We then compare the means of two samples using a paired t-test by field.

This method addresses the limitations of previous methods that there may be unobserved heterogeneity and the treatment assignment is not random, by assuming that closely located cells have only marginal differences in site characteristics, and that the treatment assignment is independent of other cell characteristics.

Results

Linear regression results

In the estimated model for the linear regression method, the outcome variable is the gross margin ($/ac) and we control for variables that assign the treatment, NDVI and YH levels, as well as field fixed effect, in-season growing degree days, total precipitation, and site characteristics; along with available water storage, soil organic carbon, and the national commodity crop productivity index (NCCPI) of corn (as a measure of site soil quality).

The results (Table 3) indicate that the effects of each method are heterogenous across fields. The magnitude as well as the signs of the coefficients differ substantially. The prescription based on NDVI outperformed the YH in 30% of fields and the YH outperformed NDVI in 40% of fields. In 30% of cases, they were not statistically different at 90% confidence level.

Table 3 Linear Regression Estimated Coefficients and their p-values of Treatment Variables by Prescription

Variable	Farm	Field	Coefficient (clustered standard error)		NDVI – YH (clustered std. err.)
			Treat 1 (NDVI)	Treat 2 (YH)	
$treat_j$	MI_A	1 (Baseline)	12 (22)	-22 (6)	34* 18
$treat_j * Field\ Fixed\ Effect$	MI_A	2	190*** (24)	-13** (6)	204*** (20)
	MI_A	3	46 (30)	119*** (15)	-74*** (28)
	MI_B	1	-95*** (29)	-37*** (15)	-58** (30)
	MI_B	2	21 (21)	21*** (7)	1 (21)
	MI_B	3	-47 (43)	-59*** (9)	12 (37)
	MI_B	4	-113*** (37)	-46*** (10)	-67** (32)
	IN_B	1	-118*** (34)	-5 (9)	-114*** (29)
	IN_B	2	16 (38)	-28*** (10)	43 (30)
	IN_B	3	37 (28)	-49*** (11)	86*** (20)

***, **, ** indicate significance level at less than 1%, 5%, and 10% respectively

Spatial discontinuity design results

We sample adjacent pairs that received the same nitrogen rate while the information source used for the prescription differs. A total of 501 pairs satisfied the conditions to be compared, although the number of pairs varies across fields. Four fields had fewer than 30 pairs, raising concerns about the statistical power of the analysis and the generalizability of the findings, hence underscoring the need for caution when interpreting the results.

The results indicate that NDVI outperformed YH in one field, while YH outperformed NDVI in four fields. In five fields (including all fields having fewer than 30 pairs), the difference between NDVI and YH is not statistically different from zero.

Table 4: Average yields by information sources and paired t-test results

Field (number of samples)		Average yield (bu/ac) NDVI	YH	NDVI – YH (std. err.)
MI_A	1 (163)	138	142	-4** (2)
	2 (12)	159	166	-7 (12)
	3 (34)	195	209	-14*** (4)
MI_B	1 (13)	266	267	-1 (2)
	2 (82)	246	250	-4*** (1)
	3 (4)	257	256	1 (4)
	4 (65)	212	216	-4** (1)
IN_A	1 (67)	217	213	4*** (2)
	2 (54)	215	213	2 (2)
	3 (7)	211	211	0 (10)

***, **, ** indicate significance level at less than 1%, 5%, and 10% respectively.

Linear regression and spatial discontinuity design yield consistent results in 70% of the fields. Among the fields with consistent results, YH outperformed NDVI in 57% (4 out of 7) of fields, with at least one instance showing statistical significance. Conversely, NDVI outperformed YH in 14% (1 out of 7) of fields, with at least one instance demonstrating statistical significance.

Table 5: Identified outperforming information by estimation methods

Field		Outperforming information: Regression	Spatial discontinuity
MI_A	1	NDVI***	YH**
	2	NDVI***	YH
	3	YH***	YH***
MI_B	1	YH**	YH
	2	YH	YH***
	3	NDVI	NDVI
	4	YH*	YH**
IN_A	1	YH***	NDVI***
	2	NDVI	NDVI
	3	NDVI***	NDVI

***, **, ** indicate significance level at less than 1%, 5%, and 10% respectively.

Conclusion

Variable rate nitrogen (VRN) application is widely recognized as a promising method for reducing excess nitrogen fertilizer and mitigating environmental pollution. However, the challenges associated with accurately calculating prescription rates persist. While several methods have been proposed for N rate prescription, a comparative analysis of their profitability remains scarce in the literature. In response to this gap, we examine and compare the profitability of different nitrogen fertilizer prescription methods using on-farm field data.

To accomplish this objective, we focus on two distinct information sets: early season crop vigor (NDVI) and yield history (YH). Each prescription utilizes a different information in that the information is from a different point of time. NDVI reflects the crop condition early in the current season, while YH aggregates past yield data. As the yield effect of applied nitrogen depends upon weather, the profitability of each treatment may differ, which motivates this study of ex-post profitability effects of each method.

This paper contributes to the literature in two ways. Firstly, we compare the effects of different VRN prescriptions on crop yields, a topic that has been relatively unexplored in existing research. By doing so, it provides insights into the comparative effectiveness and efficiency of information sources used for VRN prescriptions. Secondly, we develop a quasi-experiment method, using the data from an on-farm experiment and propose two novel analytical methods: linear regression and spatial discontinuity. These methods are designed to be easily expandable and replicable, allowing other researchers to apply and build upon our approach in diverse agricultural contexts.

Our analysis reveals that the effectiveness of different nitrogen fertilizer prescription methods varies considerably depending on the field. Specifically, we found that in the year 2021, the prescription based solely on YH led to the highest gross margin in four of seven fields (57%), while the NDVI-based prescription did so on one of seven fields (14%).

The inconclusive results between VRN prescription information sources based on gross margin evaluation suggest two avenues for future research. First, from a private profitability perspective, information costs should be incorporated into the analysis, because the gross margin over fertilizer costs is insufficient alone. Second, from a public welfare perspective, an improved analysis should account for the information source effect on excess N that is not taken up by the crop. This would be a first step toward determining whether excess N can play a role in identifying the preferred information source for nitrogen fertilization.

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Appendix

Table 4 Nitrogen prescription algorithm

Assignment criteria			Prescribed level of N	Chosen information
NDVI	YH, Stability			
High	High		High	-
	Medium		High	NDVI
	Low		Low	YH
Medium	High		Medium	NDVI
	Medium		Medium	-
	Low	Stable	Medium	NDVI
		Unstable	Low	YH
Low	High		Low	NDVI
	Medium	Stable	Medium	YH
		Unstable	Low	NDVI
	Low		Low	-