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Economically Optimal Nitrogen Side-Dressing Based on Vegetation Indices from Satellite Images Through On-Farm Experiments

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ECONOMICALLY OPTIMAL NITROGEN SIDE-DRESSING BASED ON VEGETATION INDICES FROM SATELLITE IMAGES THROUGH ON-FARM EXPERIMENTS

by

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Optimal N fertilizer rates for corn (*Zea mays* L.) vary substantially within and among fields, and by corn growth stages. Improving N side-dressing management can improve fertilizer use efficiency, farmers' profitability, and the sustainability of crop production. The objective of this study is to introduce a framework along with a methodology that can find the site-specific economically optimal N rates (EONRs) within one field for a particular growing season. An on-farm experiment was conducted in the 2019 corn growing season. A base N rate was applied uniformly on the field. NDRE images from the Sentinel-2 satellite were observed during the V10 to V12 corn growth stages. Experimental side-dressing N rates ranging from 0 to 177 kg N/ha were applied. The marginal return of N fertilizer was calculated using estimated yield response functions assuming various NDRE levels. Consistent with agronomic expectations, results showed that the parts of the field with lower NDRE values had higher marginal returns from side-dressing N, and the areas with the higher NDRE values needed less N fertilizer to reach their yield plateaus. Simulations predicted that compared to the side-dressing strategy the farmer would have implemented if not participating in the OFPE, profits could have been increased by $54.85 per hectare by using the methodology presented, applying site-specific optimal N side-dressing can increase $ 4.53 per hectare compared to applying

field-level optimal N. Results may vary under different base N and weather situations. Further study is needed to improve the featured methodology, for example, by considering adding covariates and finding better data resources for vegetation index maps.

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Introduction

The optimal nitrogen (N) fertilizer rate for corn (*Zea mays* L.) varies substantially within and among fields, but it also varies by growth stages caused by both supply of N from the soil and the crop's demand for N (Malzer et al. 1996; Harrington, Nafziger, and Hoeft 1997; Dickson, Hendrickson, and Reid 2000; Bausch and Diker 2001; P. C. Scharf and Lory 2002). In agricultural productions, lower yield may be caused by under-fertilization (Mamo et al. 2003; Magney, Eitel, and Vierling 2017). However, excess N application may cause nitrogen to leach into the soil (Cameron, Di, and Moir 2013), pollute groundwater and surface water (Miao, Stewart, and Zhang 2011; Meisinger and Randall 1991), and emit greenhouse gas to the atmosphere (Fowler et al. 2013).

The application of precision agriculture (PA) is to identify variations of input needs in the field and to address them. This could reduce and optimize the use of resources and thus can promote a higher economic return for farmers and a better environment for humans (Stafford 2000; Zhang and Kovacs 2012). Site-specific nitrogen side-dressing is a promising precision agriculture practice that provides fertilizer closer to the time when it is needed by the crop and provides different amounts of fertilizer to each individual plant according to its own demand. Unlike one-time base applications, side-dressing has more flexibility to address weather variability after planting and offers a better-synchronized fertilizer availability according to the crop's nutrient uptake (Rutan and Steinke 2018). For example, it can avoid wet spring-caused N losses and improve fertilizer efficiency by applying accurate in-season crop fertilizer demand rates (Silva et al. 2005). Site-specific nitrogen side-dressing has been gaining much attention recently thanks to technologies that make necessary information more easily accessible to support fertilizer decision makings. For example, satellite images, aerial photos, chlorophyll meters, and canopy sensing are commonly used options for side-dressing applications (Warren and Metternicht 2005; Zhang and Kovacs 2012; Stafford 2000; Dickson, Hendrickson, and Reid 2000). They could monitor crop growth status as well as input stresses, and thus provide growers with tools to detect crop N deficiency and guide N managements. The ability to detect crop N status right before N side-dressing can help with ensuring that the crop N demand is satisfied and also avoiding a surfeit of N application.

As side-dressing becomes more and more widespread, there has been substantial interest in improving the efficiency of nitrogen use by crops in the last couple of decades. P. C. Scharf et al. (2011) provided evidence that sensor-based N application rates performed better than nitrogen rates chosen by farmers. There are also substantial works that have shown evidence that optimal nitrogen fertilizer rates for corn vary substantially within and among fields, and side-dressing or site-specific fertilization could help with profit maximization (P. C. Scharf and Lory 2002; Ruffo et al. 2006; Hively et al. 2009; Franzen et al. 2016; Paiao et al. 2020; X. Wang et al. 2021).

The variability of nitrogen needs among fields has been recognized and attempted to address by previous studies (P. Scharf et al. 2002; P. C. Scharf and Lory 2009; Kitchen et al. 2010). Sufficiency Index (SI) has been widely used to help with N side-dressing rate decision makings (Varvel et al. 2007; Holland and Schepers 2010). However, by setting up the N-rich reference area and calculating the SI, the recommended side-dressing N rates usually target to achieve the yield potential or maximizing yield, instead of using fertilizer more efficiently and maximizing profits. Besides maximizing yield, P. C. Scharf and Lory (2002), Dellinger, Schmidt, and Beegle (2008), Barker and Sawyer (2010), and X. Wang et al. (2021) proposed field-level economically optimal side-dressing N rates based on corn and fertilizer prices. However, various in-season N has been uniformly applied to each field in these studies. In other words, previous studies have been mainly focusing on addressing the variability of nitrogen needs among fields and providing the field-level variable rates of nitrogen fertilizer. In order to further recognize and address the variability of optimal N rate within a field, the potential of using different Vegetation Indices (VIs) for estimating crop parameters has been analyzed and compared (Hunt Jr et al. 2011; Magney, Eitel, and Vierling 2017). They showed that VIs that measure light reflectance have the potential of providing N side-dressing needs across a field due to their ability to indicate leaf chlorophyll concentration and therefore, indicate the crop N content (Raun et al. 2002; Inman et al. 2007; Shanahan et al. 2008; Shaver, Khosla, and Westfall 2011; Montealegre et al. 2019; Tilling et al. 2007). Nevertheless, those papers only confirmed if yield values, crop N uptake, and VIs are correlated or not, and tested how good the VIs are as proxies for crop N status. Although X. Wang et al. (2021) showed that it is promising to use machine learning (ML) methods to improve corn N management on a split-plot scale, there is very limited research providing site-specific recommendations for the amount of fertilizer that should be applied for side-dressing in each individual site. As a result, further refining fertilizer decision algorithms is needed for farmers to make site-specifically in-season N fertilization decisions. Thus, this paper aims at filling up the gap of the lack of appropriate decision support systems for site-specifically in-season N applications.

Due to the development and accessibility of variable rate devices, farmers and researchers are able to conduct on-farm experiments at a field scale (Bullock et al. 2019; Kyveryga 2019). This allows researchers to explore the potential of using precision agriculture technologies to detect yield variability patterns and provide fertilizer recommendations; and farms can make decisions based on recent data from their own fields, which will lead to improved productivity and higher economic returns (Alesso et al. 2019; Laurent et al. 2019; Kyveryga 2019). The on-farm precision experimentation (OFPE) in Illinois provided the data as well as the feasibility of this study: finding the economically optimal N side-dressing rates across a field.

The objective of this paper is to develop a framework and an algorithm that can provide recommended site-specific economically optimal nitrogen rate (EONR) within a field to corn producers so that the highest profit can be achieved. Side-dressing data from a field in Effingham County, IL in the 2019 corn growing season, as well as Normalized Difference Red Edge (NDRE) index collected from satellite during V10 to V12 corn growth stages are used to meet the objective of this study. The Shape constrained additive model (SCAM) approach is used to estimate the production function. Estimated yield in each site, corn price, nitrogen price, and side-dressing N rates are used to calculate the optimal level of site-specific N side-dressing rates. Economically optimal N rates (EONR) are determined as the side-dressing N that can provide the highest economic return.

Results indicate that the marginal impact of a change in N side-dressing rate on corn yield significantly depends on observed NDRE values. In the experimental field of this study during the 2019 corn growing season, the optimal N side-dressing rates by sites are positively correlated with the NDRE values observed on June 30th, 2019. According to the results, there are a substantial number of the sites that have optimal side-dressing N rates less than the maximal side-dressing N rate in this experiment, with optimal side-dressing N rates ranging from 135 to 176 kg/ha. And a higher estimated profit can be observed by applying site-specifically side-dressing N, compared to uniformly applied N. In addition, the algorithm is further evaluated with different NDRE values and N side-dressing rates. Results show a wide range of the optimal N side-dressing rates across the field, which showed evidence of the feasibility of the algorithm providing site-specific economically optimal side-dressing N rates to farmers.

Conceptual Framework

The ultimate goal of this study is to find the economically optimal side-dressing nitrogen amount site-specifically based on vegetation index values that vary across fields, instead of merely confirming if yield values and VI are correlated or not. To achieve this goal, two steps are vital. The first is to understand the marginal impacts of additional N on increasing yield under different current N status, and the second is to find a reliable indicator that can reflect crops' current N status.

For the first step, a yield response function based on N side-dressing rates and contains the in-season crop N status at a given level of base[1] nitrogen level is the key. Such a function may be written as follows:

$$y_i = f(N_i^s, N_i^c, \mathbf{c}_i, \mathbf{z}^{post}) \qquad (1)$$

In this equation, i indicates the ith site in the experimental field. The dependent variable, y, is the corn yield in each site. N_i^s is the N side-dressing rate. $\mathbf{c}_i$ is a multi-element vector with site characteristics that vary spatially within a field but not much temporally, such as soil sand content and elevation. $\mathbf{z}^{post}$ is a multi-element vector of the weather information after side-dressing, which varies temporally but not much spatially within a field. N_i^c is the corn N content right before side-dressing, which depends on N content existing in the soil before the base application (N_i^e), N base rate (N_i^b), whether

[1] The base N in this experiment was uniformly applied to all subplots.

applied before or during planting, soil characteristics ($\mathbf{c}_i$), and pre-side-dressing weather ($\mathbf{z}^{ante}$):

$$N_i^c = g(N_i^e, N_i^b, \mathbf{c}_i, \mathbf{z}^{ante}) \qquad (2)$$

A two-stage maximization problem can be shown in the two functions stated above. The first stage is to determine the time and rates for the base N and the second stage is to determine the time and rates for the side-dressing N. In this paper, base N is treated as given and only focuses on solving the second-stage maximization problem.

Based on correlations between vegetation indexes (VIs) and crop N status found in previous studies, VIs showed promising to be used as an indicator of crop N status (K. Wang, Huggins, and Tao 2019; Paiao et al. 2020; Bausch and Diker 2001; Shaver, Khosla, and Westfall 2011), and therefore used as the signal to provide crop N information. Thus, VI can be a good proxy for N_i^c, the crop N content right before side-dressing. Then, the understanding of the impact of side-dressing N fertilizer on corn yield at different VI levels becomes the key.

Once the N content before side-dressing, N_i^c, is quantified using the VI proxy, the following second-stage profit maximization problem can be solved:

$$\max_{N_s^i} \ \Pi_i = P_c * f(N_i^s, N_i^c, \mathbf{c}_i, \mathbf{z}^{post}) - P_N * (N_i^s + N_i^b) \qquad (3)$$

Where P_c and P_N are the prices of corn and nitrogen fertilizer, respectively. The first term on the right-hand side of the equation is the revenue from corn production in site i. The second term of the equation is the cost of the base N plus the side-dressed N fertilizer in each site. N_i^b is fixed (the same for all the sites within the field) and known at the time of determining the side-dressing N rate. Since the Sentinel-2 satellite images are free to the public, the cost of acquiring NDRE data is assumed to be zero.

The first-order condition to the above profit-maximization problem is as follows:

$$P_c \cdot \frac{\partial f(N_i^s, N_i^c, \mathbf{c}_i, \mathbf{z}^{post})}{\partial N_i^s} = P_N \qquad (4)$$

The above condition states that the maximum profit is achieved when a change in revenue is zero. In other words, when one more unit of nitrogen is applied, the increased revenue ($P_c * \Delta y$) is the same as the cost of the additional unit of nitrogen (P_N).

Figure 1 illustrates the concepts visually that economically optimal N rates are different on different yield response curves based on VI values.

Literature Review

In the precision agriculture literature, there has been much work done regarding the improved efficiency of nitrogen fertilizer use, especially using crops' current N status to support in-season fertilization decision making (T. M. Blackmer and Schepers 1996; Dellinger, Schmidt, and Beegle 2008; Holland and Schepers 2010; Williams et al. 2010; Zhang and Kovacs 2012; Franzen et al. 2016; Khalilian et al. 2017; Paiao et al. 2020; X. Wang et al. 2021). The most traditional method of estimating crops' nitrogen needs was taking samples of plants and soil and then performing chemical testings (Magdoff 1991). However, this requires considerable repeated sampling and time for laboratory analysis, which may be expensive and cause a delay in fertilizer application (Dickson, Hendrickson, and Reid 2000).

In the effort to overcome the weakness of testing plants and soil samples, researchers have been using optical sensors to indicate crop N status searching for useful information for in-season N fertilizer decision makings (Wood et al. 1992; Hansen and Schjoerring 2003; Oliveira et al. 2013; Yuan et al. 2016; Padilla et al. 2020). Hand-held chlorophyll meters, for example, SPAD-502 (T. Blackmer and Schepers 1995; Padilla et al. 2018), is one of the commonly used optical sensors (T. Blackmer and Schepers 1995; P. C. Scharf, Brouder, and Hoeft 2006; Hatfield et al. 2008; Yuan et al. 2016). However, despite their abilities to measure crop N status and provide the results quickly, the measured area is generally small and further calibration is usually required, so creating appreciable replication and measurement protocols could be challenging for farmers and researchers (Shanahan et al. 2008; Monostori et al. 2016).

Considering the limitations of using chlorophyll meters, reflectance sensors have shown the advantages of providing crop status stably and reliably in a much larger area. For example, GreenSeeker, a commercially available optical sensor by Ntech Industries, can be mounted on tractors and make continuous “on-the-go” measurements across fields (Govaerts and Verhulst 2010; Padilla et al. 2020). Because chlorophyll absorbs and reflects different bands of light over the spectrum (Knipling 1970), reflected energy from crop leaves can estimate chlorophyll concentration, and therefore reflect crop N status (Haboudane et al. 2002; P. Scharf et al. 2002; Khalilian et al. 2017; Paiao et al. 2020). Two main ways have been discussed in previous studies of using reflectance sensing as the indicator to direct various optimal in-season N application rates (Raun et al. 2002; Dellinger, Schmidt, and Beegle 2008; Schmidt, Dellinger, and Beegle 2009; Holland and Schepers 2010). The first one is to compare nitrogen-deficient plots and nitrogen-sufficient plots. Because nitrogen-deficient corn reflects more light over the visible spectrum than nitrogen-sufficient corn (T. M. Blackmer, Schepers, and Varvel 1994), the larger the difference in colors between unfertilized field and well-fertilized field, the more side-dressing N is recommended by the studies (P. Scharf et al. 2002; Kitchen et al. 2010). For example, the sufficiency index (SI), which can be calculated as the ratio of the N-rich reference area and response plot areas using VI values, has been widely used to find the recommended N fertilizer rates Kitchen et al. (2010). However, the optimal N rates that have been found in those studies are the N rates reach the yield potential while maximizing the yield. Without considering the cost and marginal returns of side-dressing N, those agronomic-optimal N rates (AONR) are higher than the economically optimal N rates that can maximize profits, which is more desirable by farmers.

The second one is to find the optimal N rate from the yield production function: the optimal side-dressing N rates were driven either at the point when yield reaches the plateau (Sripada et al. 2006), or as the N rate corresponding to the maximum return based on corn and fertilizer prices (P. C. Scharf and Lory 2002; Dellinger, Schmidt, and Beegle 2008; Barker and Sawyer 2010; X. Wang et al. 2021). In the first case, again, AONR with a higher N rate was generated instead of EONR. The second case is similar to the conceptual steps that have been discussed earlier. However, those studies have only focused on finding the various EONR for different fields at different locations but haven't well addressed the variabilities of EONR within a field.

The strong relationships between VIs and crop N status found in previous studies (Bausch and Diker 2001; Sripada et al. 2006; Inman et al. 2007; Paiao et al. 2020) have shown the ability of VIs to determine crop N variability across fields and to be used as a proxy for canopy N content (Shaver, Khosla, and Westfall 2011; Magney, Eitel, and Vierling 2017), which provided a bridge for more efficient N within-field management (Hively et al. 2009). As the variability of N needs across a field has been driving more attention, a wide variety of VIs for estimating crop parameters have been analyzed (Hunt Jr et al. 2011). For example, in Magney, Eitel, and Vierling (2017)'s work, 14 out of 17 VIs were significantly correlated with the N uptake. Sensor-based NDVI values showed significant relationships with applied N rates ($r^2 > 0.89$) in Shaver, Khosla, and Westfall (2011)'s work. Tilling et al. (2007) found that NDRE is able to account for 68% of the nitrogen stress index and 41% of crop N status in a wheat field. These consistent results indicated that VIs could be potentially used as the signal, which has been discussed earlier in the conceptual steps, to indicate crops' current N status and then help with N fertilizer decision makings.

Recently, the NDRE index has shown a better performance as a measure of crop nitrogen content than other commonly used VIs, and a strong agreement with the actual harvest N uptake values and NDRE nitrogen uptake models has been observed in previous studies (Magney, Eitel, and Vierling 2017; K. Wang, Huggins, and Tao 2019; Argento et al. 2020; X. Wang et al. 2021). Magney, Eitel, and Vierling (2017) used high-resolution satellite data to evaluate the relationships between VIs and N uptake. Results showed that NDRE index performed the best (R^2 = 0.81, RMSE = 15.94) out of 17 commonly used spectral VIs, followed by NDVI index (R^2 = 0.71, RMSE = 20.96). These results are consistent with the findings in Zillmann et al. (2015), Magney, Eitel, and Vierling (2017), K. Wang, Huggins, and Tao (2019), and Paiao et al. (2020). However, in spite of the correlation between VIs, especially NDRE, and crop N status has been widely recognized, without proposing how to provide EONR for the next growing season, the implication has been stagnated as showing the potential of using NDRE for improving N use efficiency. How to use this information in real agricultural activities is still unclear. According to Schimmelpfennig (2016), in the United States, only 30-40 percent large[2] corn farms adopted precision agricultural technologies, and most of them are just using yield monitors. There is a large room for developing and adopting variable-rate technologies on farms.

[2] The size of the farm is over 1,174 Hectares

In summary, there have been substantial studies done related to N side-dressing activities. The evidence indicates that vegetation indices observed from remote sensing show promise in providing crop nitrogen status and N side-dressing needs (Inman et al. 2007; Hunt Jr et al. 2011; Magney, Eitel, and Vierling 2017). However, the studies providing optimal in-season nitrogen rates for cornfields only recognized the variable-rates among different fields (P. C. Scharf and Lory 2002; Dellinger, Schmidt, and Beegle 2008; Kitchen et al. 2010), but ignored the variability of nitrogen needs within one field. Moreover, past literature worked on improving site-specific N decision makings have been only focusing on testing the explanatory power of the VIs to crop N status and checking how accurate the VIs are in helping to make N side-dressing decisions (Bausch and Diker 2001; K. Wang, Huggins, and Tao 2019; Paiao et al. 2020). To the author's knowledge, so far, there are no studies have developed practicable algorithms that provide site-specifically EONR within individual farms to farmers. There is a clear need to further refine fertilizer decision algorithms and fill up the gap of lacking appropriate N side-dressing decision support systems. In this study, a crop simulation model is estimated using side-dressing data from Effingham County, IL and NDRE values collected from the sentinel-2 satellite. According to the production function, corn yield can be simulated with each level of NDRE and N side-dressing rate. Thus, profits can be estimated, and optimal N side-dressing rates can be selected by a given corn price and N price.

Materials and Methods

1. Data

In 2019, the Data Intensive Farm Management project (DIFM, (Bullock et al. 2019)) conducted an on-farm experiment on a 31.22-ha Illinois field, which generated this study's data on corn yield response to nitrogen fertilizer application rates. The participating farmer planted corn on May 16th, 2019 and harvested on October 19th, 2019 using a CaseLH 8240 combine with a 12-row corn head. He applied an N base of 135 kg/ha uniformly across the field. Figure 2 shows that the experimental N side-dressing rates ranged of from 0 to 177kg/ha. Data from 9-meter buffer zone around the perimeter of the field was excluded from the experiment. The interior of the field was partitioned into twenty-two 8.8m-wide strips, each containing approximately 85 subplots, which were treated as units of observation. As a result, the trial was partitioned into 1867 subplots with an average size of 0.0167 ha. Urea ammonium nitrate (UAN, 32% N) was applied as the side-dressing N to the soil surface on July 16th, 2019 by DMI anhydrous applicators. The field's 2019 growing season's minimum and maximum temperatures of 14.9°C and 26.6°C were close to the 1999-2019 averages; its 855mm precipitation was higher than the 611m 1999 to 2019 average. Figure 2 shows each subplot's mean as-applied side-dressing rate and yield.

The Normalized Difference Red Edge index (NDRE) (Barnes et al. 2000; Rodriguez et al. 2006) is a vegetation index related to the red edge reflectance obtained from multispectral image sensors. NDRE is calculated as:

$$NDRE = (R_{NIR} - R_{RED\ EDGE}) / (R_{NIR} + R_{RED\ EDGE}), \qquad (5)$$

where R_{NIR} and $R_{RED\ EDGE}$ refer to near-infrared bands (790 nm) and red-edge bands (720 nm), respectively. The R package, sen2r (Ranghetti et al. 2020), was used to acquire 10-m resolution NDRE images from the European Copernicus Program's Sentinel-2 satellite (Sentinel 2015). The participating farmer planted on May 17th. At the field's latitude, corn reaches the V10-V12 growth stages around eight hundred growing-degree days after planting (Lee and others 2011). The NDRE data mapped in Figure 3 were taken from June 30th, 2019 images, based availability from Sentinel-2. Growth stages were verified using the Midwestern Regional Climate Center's decision support tool (U2U@MRCC, n.d.). Table 1 presents summary statistics of the yield, NDRE, side-dressing (N), electro-conductivity (ECS), elevation (DEM), and slope levels.

2. Method

Site-specific corn production function was estimated by regression using shape constrained additive model (SCAM) using the scam package (Pya 2020) in R (R Core Team 2020). Among commonly used VIs, NDRE (Barnes et al. 2000), has been selected due to its better performance as a measure of crop nitrogen content shown in the previous studies (Magney, Eitel, and Vierling 2017; K. Wang, Huggins, and Tao 2019; Argento et al. 2020). Statistical analyses and regression are performed with R programming.

In order to test the impact of different values of NDRE on corn yield, four NDRE intervals are divided based on each 25 percentile of its distribution. Assuming that if observed NDRE values fall into a same range, the marginal impact of side-dressing N on yield stays the same. In this case, by using NDRE as the proxy for plants' current N content, the interactions between side-dressing N rates and different crop current N status become observable. Thus, all fields plots are partitioned into four groups according to their NDRE levels and the yield response functions in each NDRE level are assumed to take the functional form in (6):

$$y_i = f(N_i^s) + g(ECS_i) + k(TPI_i) + h(elevation_i) + m(X_i) + n(Y_i) + j(X_i * Y_i), (6)$$

where the response variable, y_i, represents corn yield in each subplot. Independent variables included site-specific nitrogen side-dressing rates (N_i^s), shallow soil electrical conductivity (ECS_i), topographic position index (TPI_i), and elevation values derived from digital elevation models ($elevation_i$) are included in the model. X_i and Y_i are geographical controls for longitudinal and latitudinal spatial changes, respectively. By comparing the four yield response functions based on the four groups of NDRE levels, different marginal impacts of side-dressing nitrogen on yield under different NDRE levels can be observed. Higher side-dressing nitrogen rates are expected to associate with higher yield levels. More importantly, as discussed earlier, the different slops of the yield response functions could show how the marginal impact of side-dressing nitrogen rates on corn yield associate with NDRE levels in each plot. Given this information, EONR can be selected when the marginal return of one more unit of N equals its marginal price.

The profit maximization problem for each plot i is as follows:

$$\max_{N_i^s} \ \Pi_i = P_c * y_i - P_N * N_i^s \qquad (7)$$

The inflation-adjusted average historical corn price in Illinois of \$0.157 kg^{-1} and an N price of \$0.88 kg^{-1} were assumed. Side-dressing rates considered were bounded by the experiment's maximum and minimum targeted rates.

Results and Discussions

According to the regression results, side-dressing rates are statistically significant at 1% level for all zones with four NDRE levels. Unlike traditional regressions, the regression results of non-parametric regression are best presented using figures as the individual coefficients themselves are not meaningful. Figure 4 presents the regression results of the SCAM estimation of the yield response function. It shows the impact of N side-dressing on corn yield at four different NDRE levels. As expected, N side-dressing rates positively affect corn yield and NDRE values significantly influence the marginal impact of N fertilizer on yield. Specifically, the marginal benefit on yield decreases when NDRE gets higher, reflected by the decreasing slopes when NDRE levels increase.

Based on the production functions, at a side-dressing N rate lower than 125 kg/ha, the yield is lower for the parts of the fields with lower NDRE. This is consistent with agronomic expectations because a lower NDRE value indicates a more significant N deficiency, then the parts of the fields with lower NDRE should have lower yields. Due to the objectives of this study is to maximize farmer's profit instead of reaching the yield potential, as discussed earlier, *the marginal impact of a change in side-dressing N rate on yield is more important here*. Despite the marginal return of side-dressing N is quite high for the area with the highest NDRE level when side-dressing N rates are lower than 75 kg/ha, the marginal impact of N is generally greater for parts of the field with lower NDRE values. For example, increasing N side-dressing rates from 55 to 130 kg/ha can help increasing corn yield by 2573 kg/ha (from 10671 to 13244 kg/ha) in the subplots with the lowest level of observed NDRE values. However, the same amount of side-dressed N can only increase corn yield by 1444 kg/ha (from 13621 to 15065 kg/ha) if the observed NDRE values fall in the highest level. In other words, when NDRE values are less than 0.241, the yield response function had the highest slope, which indicates that the side-dressing N showed the highest marginal effect in increasing corn yield. This is consistent with agronomic expectations because a lower NDRE value indicates a more significant N deficiency, adding in-season N then has a more marginal impact on corn yield. When the NDRE value is less than 0.333, the marginal impact of N on corn yield stays positive with less marginal returns of N, compared to the areas that have the lowest NDRE, and the economic optimal N rates are the maximum amount of N applied in the experiment. When the NDRE value is higher than 0.333, corn yield reaches the plateau when the N rate is 135 kg N/ha. This is again consistent with agronomic expectations because a higher NDRE value indicates a less significant N deficiency, requiring less N to reach the yield plateau. The areas having high observed NDRE values showed high N marginal return when side-dressing N rates are lower than 75 kg/ha. This could because the soil in high NDRE areas has a better capacity of absorbing N. Thus, after applying side-dressing N fertilizer, the crops can get N and reach the yield potential quickly.

The result of the negatively correlated relationship between Vegetation Indies and EONR is consistent with previous works (Sripada et al. 2006; Dellinger, Schmidt, and Beegle 2008). However, as discussed earlier, previous studies have been mainly addressing the variability of N needs among fields and only finding the average EONR for each field. So, the in-season N recommendations for corn proposed earlier are determined at a field scale. Even though different N needs within fields have been recognized (Malzer et al. 1996), it is still difficult to predict the EONR at a subplot or subfield scale (Dellinger, Schmidt, and Beegle 2008). This study takes the recommendation of in-season N a step further. The experiment of this study is conducted within one field and the variability of EONR is addressed across the field. By dividing the whole field into many 0.017-hectare plots and then group those plots based on their observed NDRE values, farmers can apply different amounts of recommended N to each subplot according to its own N demand. Although some of the chlorophyll meters and on-the-go sensing devices have been used to attempt to address N variability within fields, again, most of them focused on finding the side-dressing N rates that can reach the yield potential. Compared to applying N uniformly within the field or maximizing yield, the method proposed in this paper can apply N fertilizer at the places where the highest N marginal benefits can be returned, which could provide more economic and environmental benefits. This is consistent with the expectations and results by Bullock et al. (2019).

As stated earlier, the key goal of this study is to provide site-specific side-dressing N rate recommendations to farmers based on observed NDRE values. The map of EONR in the experiment field is presented in Figure 5. As can be observed in the figure, EONR rates vary substantially across the field. This implies that there is a room to improve N use efficiency via NDRE-based site-specific N side-dressing, which in turn can mitigate the environmental consequences of N over-application. Moreover, the results showed that 142 kg/ha is the optimal uniformly applied in-season N rate in this field during the 2019 corn growing season, which could provide the maximum net revenues of $2236 per hectare. While, under the same condition, the average of site-specific EONR is 162 kg/ha, and it could provide an estimated net revenue of $2317 per hectare. These results matched with the expectations of this study that the site-specific side-dressing can ensure more N fertilizer is applied at the place, within the field, where it is needed and therefore increase the corn yield and economic returns.

Differing marginal impacts of side-dressing nitrogen rate results in heterogeneous optimal side-dressing amount based on NDRE. Table 2 shows how the economically optimal nitrogen rate changes according to the value of NDRE. While the EONR goes up slightly when NDRE increases from the lowest level to the second-lowest level, EONR goes down as NDRE increases after $NDRE = 0.288$. In addition, EONR significantly dropped when the subplots have NDRE values higher than 0.333. This further proved the feasibility of providing side-specific side-dressing N rates using the algorithm proposed in this study.

However, NDRE is not a pure indication of the lack of N. The "greenness" of a crop is not just affected by its N concentration, but also many other factors, for example, environment, illumination, disease, soil type, soil properties, deficiencies of other nutrients (Rorie et al. 2011). All of these could significantly affect the productivity of fields and crops' yield potential. If, for example, a field is large enough or there are more heterogeneities within a field, different areas of the field may have different productivities due to the conditions of nutrients other than N. Then the nutrient sufficient subplots may have higher NDRE values, but higher side-dressing N rates are still needed to reach the higher yield potential than the nutrient-deficient subplots. In this case, economically optimal N rates could be positively correlated with NDRE.

In previous studies, N Sufficient Index (SI) or relative colors have been commonly used to find optimal N rates Barker and Sawyer (2010). Sripada et al. (2006) had a consistent result with P. C. Scharf and Lory (2002) that absolute VIs are not significant predictors of EONR so that a high-reference is necessary to predict N needs. This is because the correlations were tested between EONR and VIs among different locations under different irrigation and soil type conditions. As discussed earlier, the yield potential and absolute colors among different fields may be very different and not relevant. Since the algorithm suggested in this study is using the NDRE observed in one field and providing site-specific EONR within the specific area, establishing reference plots and calculating sufficiency values is not required. But instead, this method requires farmers to find each field's yield response function and be consistent with the ways of observing NDRE values.

134 kg/ha base N is applied in this field. However, results will vary with different amounts of base fertilizer application, and residual soil N. Other environmental and water stresses can affect corn yield response to N. During the 2019 corn growing season, precipitation was slightly higher than the twenty-year average and temperatures were very close to the average levels. Results are likely to be different during drought years or having extreme heat. Weeds, pests, the mixture of soil could be other factors that influence the performance of this method; for example, more weeds may increase the NDRE values and then reduce the recommended optimal N side-dressing rates. Optimal N side-dressing rates could also be influenced by field management practices such as irrigation management, planting dates, inherent soil variability, and different corn species. These variables could potentially be brought into the modeling framework

presented in this work to refine the crop yield simulation model and optimal N side-dressing rates.

Previous studies have shown the potential of using corn colors from V6 to V9 growth stages for in-season N recommendations (P. C. Scharf and Lory 2002, 2009; X. Wang et al. 2021). P. C. Scharf and Lory (2002) has discussed that V6 is the earliest stage that crop N needs can be reflected by plant colors. However, in this study, corp colors observed by 10 m resolution satellite images are not varied enough to help with making N decisions until V10 to V12. Waiting until this period to observe VIs and make N application decisions will require very time-intensive analysis before corn growing too tall for side-dressing equipment. Some special or taller equipment may be needed for fertilizer application, which could increase the cost. Applying side-dressing N at V10 to V12 growth stages may also increase the risk of reducing yield due to not applying N in time.

Satellite images acquired from the Sentinel-2 are used to calculate NDRE values in this study, which can provide more spatial information than chlorophyll meters and potentially reduce the cost due to it is free for public acquisitions. Moreover, satellite images are able to provide more consistent information in bigger-size fields without problems related to bias caused by different angles from cameras, overexposure, and film size (P. C. Scharf and Lory 2002). However, in some situations, images from unmanned aerial vehicle (UAV) or on-the-go sensing devices have advantages than satellite images if the plot size is relatively small, or higher quality and finer resolution images are required so that more accurate yield response functions and optimal N rates can be provided (Argento et al. 2020). They are also usually less restricted by weather or atmospheric conditions (Rambo et al. 2010), satellite geometry, sun-angles (Holben 1986), and soil backgrounds since they are held closely above the crops (Govaerts and Verhulst 2010). However, the costs of these kinds of reflectance sensors are usually high (Padilla et al. 2020). Nevertheless, due to the width of N fertilizer applicators, N cannot be applied very finely even the high-resolution images are available. Overall, it will be interesting for future studies to examine the trade-offs between the cost of acquiring VI values and the benefit brought from the information.

Conclusion

Despite the increasing interest in variable rates of N side-dressing based on sensor-based VIs, very little has been done to generate the site-specific economically optimal side-dressing N amount based on VIs. As argued earlier, most studies stopped either at finding the EONRs for different fields or simply confirming the correlation of VIs and N deficiency, without going further to come up with finding the VI-based site-specific economically optimal side-dressing N amount.

This study takes the recommendation of in-season N a step further with proposed a framework and method to come up with finding the VI-based site-specific economically optimal side-dressing N amount. The critical information is the quantified relationship between, yield, side-dressing N rate, and VI (here, NDRE). This study used on-farm field experiments, satellite imagery, and statistical methods to find such a relationship. The EONR is then estimated by solving site-specific profit maximization problems. Our results are consistent with agronomic expectations, where the parts with lower NDRE requiring higher amounts of side-dressing N.

A better understanding of the impacts of other environmental factors and soil properties on crop yield would be helpful to improve the quality of site-specific N side-dressing recommendations in the future. While NDRE is used as the VI, the framework laid out in this study is very much general and can be applied to any VI, such as Green Normalized Difference Vegetation Index (GNDVI). Moreover, the framework is perfectly compatible with the method of obtaining VIs. This study used Sentinel-2 data.

While it is free, it comes at the cost of low spatial resolution and more instability due to weather conditions. There exists an interesting trade-off between the qualities of the sources of VIs and their cost. It would be a fruitful study to examine the economic potential of other methods of obtaining VIs, such as drone.

Tables

Table 1: Summary Statistics

	Yield	NDRE	N	ECS	DEM	Slope
mean	12967.03	0.29	104.94	29.55	625.73	0.04
SD	2001.09	0.06	36.88	5.47	2.76	0.01
Min	4877.22	0.14	0.00	16.09	620.91	0.03
Max	17650.45	0.47	177.21	53.65	631.94	0.10

NDRE was observed on June 30th, 2019

N is the side-dressing nitrogen rate (kg/ha) applied on July 16th, 2019

Table 2: The impact of NDRE on optimal nitrogen side-dressing rate

NDRE Levels	EONR (kg/ha)
[0.139, 0.241]	165
(0.214, 0.288]	176
(0.288, 0.333]	170
(0.333, 0.472]	136

Figures

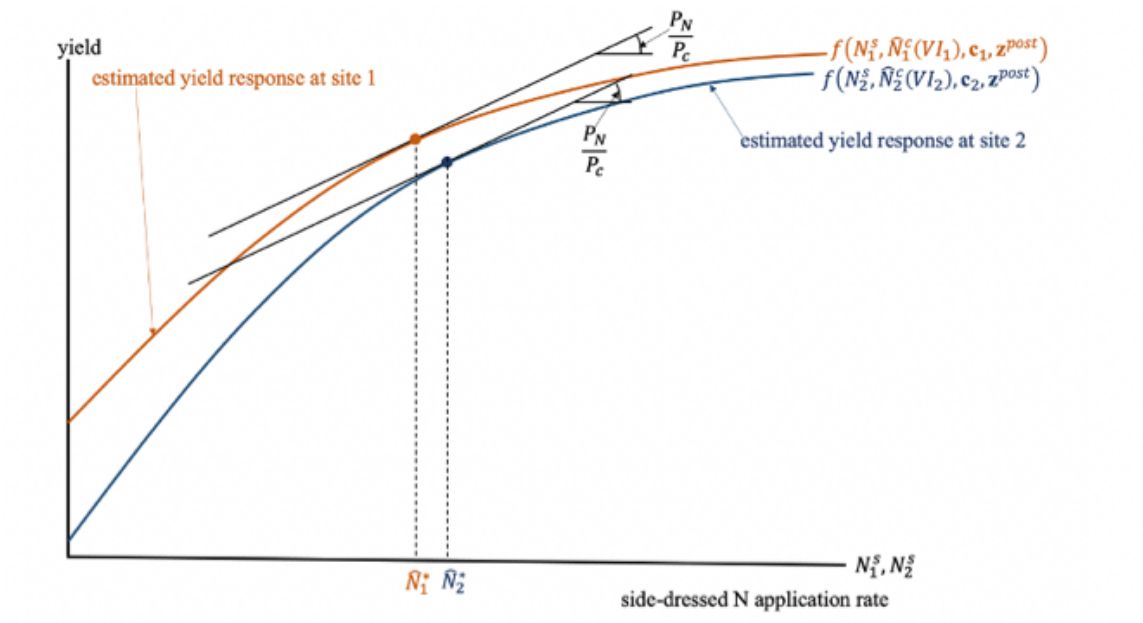

Figure 1: Estimated economically optimal side-dressing N rates, given estimates of the yield response function and of the vegetative index values

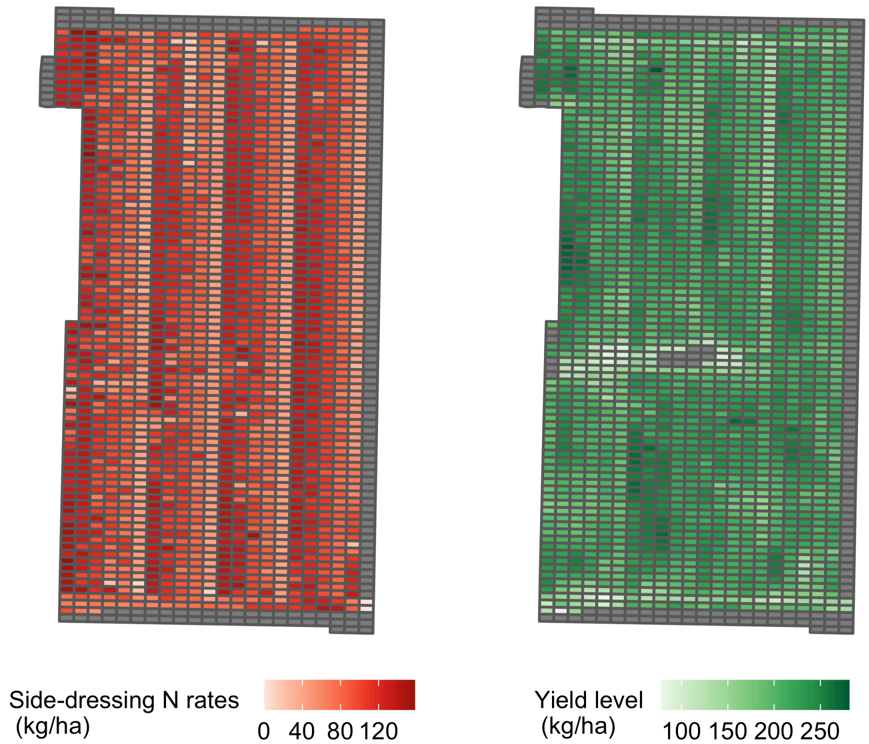

Figure 2: As-applied side-dressing N map and yield level map

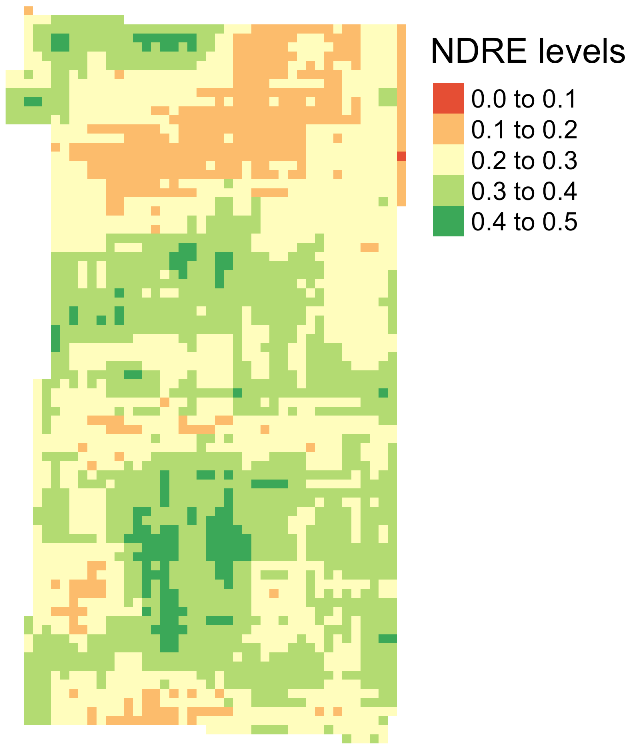

Figure 3: NDRE values observed on June 30th, 2019

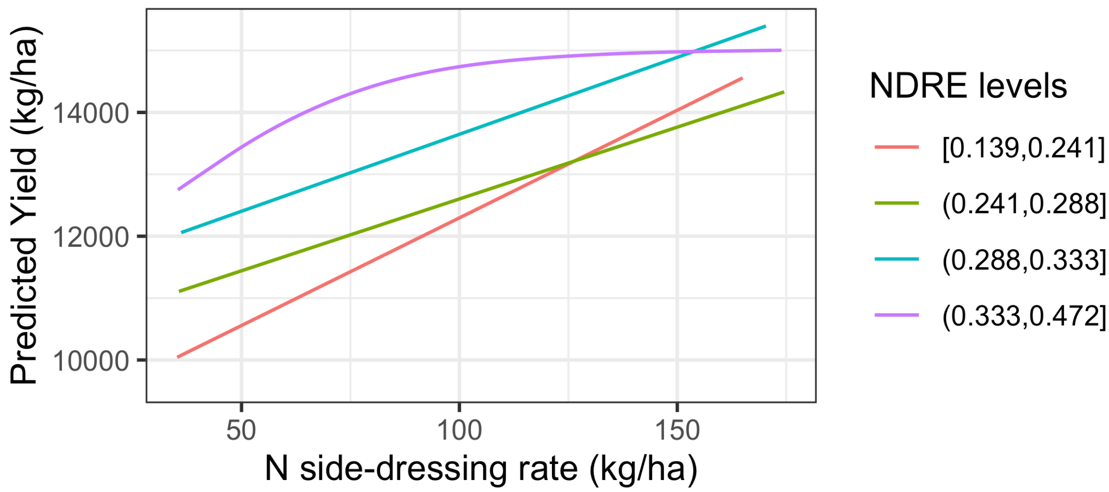

Figure 4: Yield response functions at different levels of NDRE

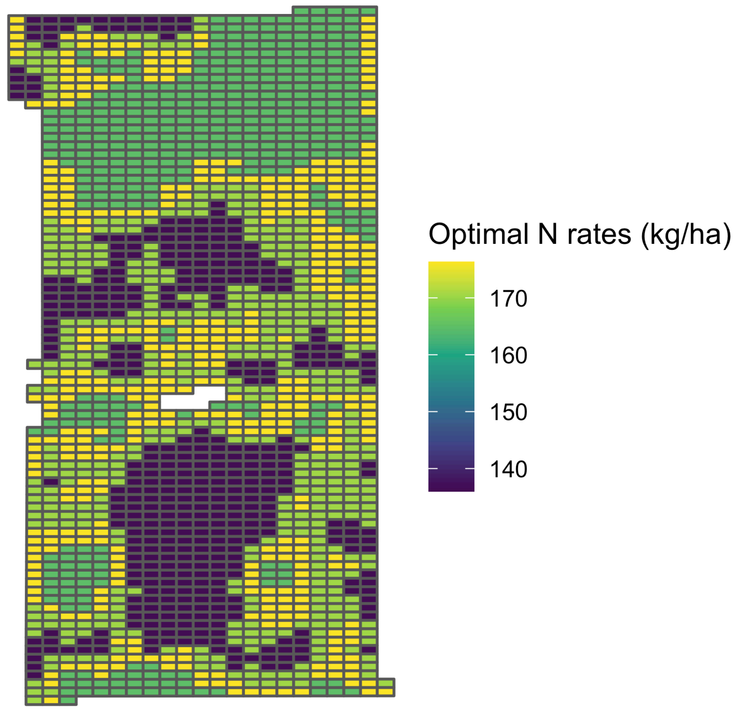

Figure 5: Optimal side-dressing N rate by subplots in the experiment in 2019

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