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Reducing Water Pollution from Nitrogen Fertilizer: Revisiting Insights from Production Economics

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ABSTRACT

Nitrogen sourced from agricultural fertilizers is a major contributor to water pollution. Despite policies targeting a range of farming practice changes, the goal of substantially reducing nitrogen losses from farms remains elusive. We highlight three empirical results from production economics that appear to provide untapped opportunities for policies to reduce nitrogen rates. First, many farmers apply more nitrogen than required to maximize expected profits or utility. Second, contrary to the perceptions of some farmers and farm advisers, nitrogen fertilizer is a risk-increasing input. Third, over wide ranges of nitrogen fertilizer rates, the relationship between rate and profit is remarkably flat, meaning that farmers can reduce fertilizer usage substantially at minimal private cost. We discuss a variety of policy options for efficiently exploiting these insights.

Keywords: water pollution, nitrogen fertilizer, optimal nitrogen rate, production risk, flat payoff function

1. **Introduction**

Worldwide, the use of chemical fertilizer grew markedly over the past half century. There was an almost six-fold increase from 32 million metric tons of nutrients in 1961 to 191 million metric tons in 2019 (IFA, 2021).[1] The geography of fertilizer use also changed dramatically. In 1961, the high-income countries (notably North America and Western Europe) accounted for 79% of the world's fertilizer use. By 2019 the rich-country share had shrunk to 25%, with middle-income countries—including large agricultural economies such as Brazil, China and India—now making up 74% percent of worldwide fertilizer use. China alone consumed 24% of the global total in 2019, compared with only 3.4% in 1961 (IFA, 2021). In contrast, the low-income countries still lag well behind in terms of fertilizer use, accounting for a tiny fraction, 0.6%, of the 2019 global total, even though they sowed 9.4% of the world's cropland that year.

The intensity of fertilizer use also increased markedly; from a 1961 world average of 25 kg per ha of cropland to 132 kg/ha in 2019 (IFA, 2021).[2] While the intensity of use for the group of high-income countries largely plateaued after the early 1980s, and even declined for Western Europe, rates of fertilizer use continued climbing at a rapid rate in Asia, particularly in China. In 2019, China applied an average of 337 kg of fertilizer per hectare of cropland, compared with 126 kg/ha in North America.

[1] Here total fertilizer use is the sum of N (nitrogen), P (phosphorus) and K (potash) consumption measured in nutrient equivalents.

[2] These average fertilizer use intensities were estimated by the authors using national level total fertilizer consumption estimates from IFA (2021) and corresponding cropland area estimates from FAO (2021). Obviously, fertilizer is also applied to areas other than cropland (e.g., permanent or cultivated pastures and meadows), but comprehensive area data for these types of land are not available. Moreover, in those countries where there are multiple crops per year, by construction these *annual average* "intensity of use" estimates overstate the actual rate of fertilizer use on an area-by-cropping-season basis. For example, if we use total harvested area (which accounts for multiple crops per year) as the measure of land, the average NPK application rate for China is 257 kg/ha (versus 354 kg/ha when cropland area is used).

Increasing both the area receiving fertilizer and the intensity of its use spurred historically unprecedented growth in crop yields and overall crop production,[3] with profound implications for global food security. On the other hand, there are significant water-pollution consequences attributable to the loss from fields of excess fertilizer in surface water or groundwater (OECD, 2012). The FAO recently stated that "[a]griculture is the single largest producer of wastewater, by volume …" (Mateo-Sagasta et al., 2018, p.xiii) and is responsible for widespread deterioration in the quality of water in rivers, lakes, aquifers and oceans. Agriculture is a key source of water contamination in the U.S. (see, for example, US-EPA, 2017; Kling et al., 2014; NRC, 2008), China (Smith and Siciliano, 2015; Jin and Zhou, 2018), and many other countries (OECD 2017). Thus, it is no surprise that poor nitrogen management in agriculture is flagged as a notable impediment to achieving one of the United Nations sustainable development goals (SDG6), specifically clean water and sanitation (Sachs et al. 2021, p.30).

Reducing agricultural water pollution has been challenging, in part because it is a geographically dispersed and non-point source of pollution but also because the agricultural inputs that cause pollution are often highly beneficial for farmers. The key agricultural pollutants causing problems in receiving water bodies are nitrogen and phosphorus, although there are also concerns about pesticides and herbicides in some cases (US-EPA, 2021). The main source of nutrients is inorganic fertilizer, but animal manure also contributes to water pollution, particularly where manure is used as a crop fertilizer (Alexander et al., 2008). Here we focus on nitrogen, which is relatively mobile in soil water. Following the microbial transformation of soil ammonia into nitrates (NO_3, a soluble salt form of nitrogen), it can be leached below the root

[3] For example, the average rate of application in the U.S. climbed from 43 kg/ha in 1961 to 127 in 2019 (1.9% per year growth), and the share of fertilized cropland grew from 28.6% to 59% (USDA various issues), while the real (inflation-adjusted) value of U.S. crop production grew by 1.7% per year (FAOSTAT, 2021).

zones of crops and pastures where it can accumulate in groundwater or discharge into streams (Hatfield and Follett, 2008).[4] Nitrogen also reaches streams via surface run-off from fertilized crop fields and pastures, via drainage tiles or roadside ditches and drains.

There is a sizable literature on the benefits and costs of measures to mitigate agricultural water pollution (e.g., Doering et al. 1999; Ribaudo et al., 2001; Kling et al., 2006; Doole et al., 2013; Hyytiäinen et al., 2015). Studies have explored the economics of a host of on-farm strategies, including reducing fertilizer rates, use of variable-rate technologies, zero till, cover crops, nitrification inhibitors, land retirement, buffer strips, and bioreactors (see Pannell et al., 2020 for a review of these studies).

Of these strategies, reducing fertilizer rates is often a relatively efficient option (Doering et al. 1999; Ribaudo et al. 2001). The other options tend to be relatively costly for farmers to adopt (cover crops, land retirement, buffer strips, bioreactors) or relatively ineffective at reducing nutrient pollution (zero till, nitrification inhibitors) (Pannell et al. 2020).

There have been various policy efforts in the U.S. to reduce fertilizer usage to mitigate water pollution, including programs that involve provision of technical information and advice, watershed planning, cost-sharing, performance standards and cross-compliance measures (Shortle et al., 2021). However, programs are costly, resource constrained, and often poorly targeted, and participation tends to be disappointing (Shortle, 2017; Shortle et al., 2021). As a result, there has been no discernible downward trend in fertilizer usage in the U.S. (Cao et al., 2018) or in nutrient delivery to impacted areas such as the Gulf of Mexico (USGS, n.d.).

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[4] Phosphorus is less mobile because it tends to bind onto soil particles (Holtan et al., 1988). For that reason, much of the phosphorus that moves from agricultural fields into water bodies does so attached to sediment that has been made mobile in surface water due to soil erosion (Muukkonen et al., 2009; Farkas et al., 2013).

Economists have undertaken a range of analyses of management and policy strategies for reducing agricultural water pollution, including in the Mississippi River watershed (e.g., Doering et al., 1999; Ribaudo et al., 2001, Kling et al., 2014), Chesapeake Bay (Wainger et al., 2013; Fleming et al., 2018), Europe (Hasler et al., 2014), and Australia (Star et al., 2018). However, economic studies that focus on the production economics of fertilizer use in agriculture in the context of water pollution are lacking. In addition, the formulation of recommendations for fertilizer-use strategies is often undertaken by agronomists or other plant scientists without quantitative consideration of production-economic issues (e.g., Austin et al., 2019).

This paper is motivated by our judgement that there are unrealized opportunities for utilizing findings and insights from production economics to reduce agricultural nutrient pollution at low cost. We highlight three important empirical results from production economics that have the potential to improve policy outcomes in this area: (a) that a substantial proportion of farmers apply more fertilizer than the rate that would maximize their expected profits; (b) that increasing fertilizer rate is a risk-increasing strategy; and (c) that the relationship between fertilizer rate and expected profit (or certainty equivalent profit) is almost flat over a wide range of commercially common fertilizer rates. Result (a) is reasonably well known but has rarely been directly exploited in water-pollution policy. Results (b) and (c) are much less well known and are likely to conflict with the preconceptions of many, including many involved in formulating fertilizer recommendations and water-pollution policy.

As we will show, the implications of these results are profoundly important. Result (a) means that there are untapped opportunities for win-win outcomes, benefiting both farmers and the environment. Result (b) means that some farmers are in error in believing that increasing their fertilizer rate above the profit-maximizing level provides benefits in terms of risk reduction, again pointing to opportunities for win-win outcomes. Result (c) means that the cost to farmers from reducing their fertilizer rate, even below the expected-profit-maximizing rate, is very much less costly at the margin than many currently believe, creating opportunities for innovative policy approaches.

In this paper we proceed as follows. In the next section we present the concepts and theories underpinning these three issues. Then we present a case study from the U.S. cornbelt. Data are described and used to estimate the effects of nitrogen fertilizer on yield, profit and risk. Based on those illustrative results, we then explore the potential for agri-environmental policy to reduce agricultural water pollution at low cost, drawing on the perspectives outlined above. Finally, potential policy responses are discussed.

2. The Production Economics of Fertilizer

2.1 Profit-maximizing Fertilizer Rate

The problem of a farmer selecting the fertilizer rate to maximize expected profit is an example of a classic production economics problem: ex ante optimization of the amount of a production input. In the simplest model, the profit-maximizing fertilizer rate is that where the marginal benefit from increasing grain yield equals the marginal cost of applying additional fertilizer. A key result is that the profit-maximizing rate is less than the yield-maximizing rate.

A common observation is that many farmers appear to apply fertilizer rates higher than the profit-maximizing rate. The following statistics are for the United States as a whole.

> "Nitrogen is applied at more than the benchmark rate on 36 percent of corn acres by an average rate of 39 lbs per acre; on 19 percent of cotton acres by an average rate of 40 lbs per acre; on 22 percent of spring wheat acres by an average rate of 30 lbs per acre; and on

> 25 percent of winter wheat acres by an average rate of 24 lbs per acre" (Wade et al., 2015, p. 19).

The benchmark rates used to derive these results were based on biological criteria rather than economic criteria (based on the USDA, National Resource Conservation Service, CEAP-Cropland project[5]). Given that economically optimal fertilizer rates are likely to be lower than biologically determined rates, the potential for rate reductions that would be financially beneficial to farmers may be even greater than suggested by the numbers provided by Wade et al. (2015). Christianson et al. (2013) also found that reductions in nitrogen fertilizer rates in the U.S. Midwest could be done at negative cost in many cases.

Various possible reasons for farmers using unnecessarily high fertilizer rates have been suggested, including that they fertilize to maximize yield rather than profit, that they misjudge the shape of the production function, or that they apply high rates to reduce production risk (see below).

2.2 Fertilizer Rate and Risk

Farmers apply fertilizer without precise knowledge of the climate and market realities that will ultimately affect the profit outcomes of their input-use decisions. The resulting risks may motivate farmers to modify their fertilizer rates. For example, if higher rates are perceived to be less risky than lower rates, then a risk-averse farmer would have an incentive to use higher rates. The issues of interest here are the direction and strength of that incentive.

[5] A list of reports from the CEAP project, including benchmark nitrogen rates, is available at http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/technical/nra/?cid=nrcs143_014144 [accessed April 4, 2022]

As noted earlier, it has been suggested that one of the reasons for some farmers applying high rates of nitrogen fertilizer is (or could be) risk aversion (e.g., SriRamaratnam et al., 1987; Sheriff, 2005). “Fertilisers can be expected to be overused due to risk aversion among farmers” (Pearce and Koundouri 2003, p.144). This implies that these farmers perceive nitrogen fertilizer to be a risk-reducing input, as observed by SriRamaratnam et al. (1987) in a survey of grain sorghum producers in Texas. However, the empirical evidence overwhelmingly shows that nitrogen fertilizer is not a risk-reducing input: if anything, yield and profit have greater variance at higher rates of nitrogen fertilizer. Examples of studies that reached this conclusion include Just and Pope (1979) (using experimental data for corn and oats in Mississippi), Nelson and Preckel (1989) (using farm data for corn in Iowa), Love and Buccola (1991) (using farm data for corn in Iowa), Roosen and Hennessy (2003) (using experimental data for corn in Iowa), Rajsic et al. (2009) (using experimental data for corn in Ontario, Canada), and Meyer-Aurich and Karatley (2019) (using experimental data for wheat in Germany). In addition to these studies, which focus primarily on production risk, we know that price risk acts to further increase overall risk at higher input rates, assuming that the input increases expected yield (Sandmo, 1971). In other words, price risk also contributes to nitrogen fertilizer being a risk-increasing input.

Although the direction of influence seems clear, the marginal rate of increase in risk is usually not high. As a result, for realistic levels of risk aversion, the differences in optimal fertilizer rates between farmers who differ only in their level of risk aversion are likely to be small (e.g., Meyer-Aurich and Karatley, 2019).

2.3 Flat Payoff Functions

Farmers' gross margins are highly insensitive to changes in input rates within the vicinity of the agronomically optimal rate[6]. This empirical fact has been known and discussed in agricultural economics for many years (e.g., Hutton and Thorne, 1955; Doll, 1972; Anderson, 1975). More recently, Pannell (2006) highlighted a number of consequences of this result for farm management and agricultural research, stimulating new interest in the issue (e.g., Rajsic and Weersink, 2008; Meyer-Aurich and Karatley, 2019).

Pannell et al. (2019) illustrate the flatness of the relationship between nitrogen fertilizer rate and crop gross margin by reporting the range of nitrogen rates with gross margins that are at least 95% of the maximum gross margin. For a case study of wheat in Germany (Pannell et al. 2019), the range is 64 to 88% of the optimal nitrogen rate, depending on various assumptions. In other words, a certain percentage reduction in fertilizer rate below the optimum results in a very much smaller percentage reduction in profits, providing further opportunities for innovative policy.

In this study, we are mostly interested in the consequences of *reducing* the N rate on farmers' profits and utility, so we identify the range between the optimal rate and a reduced rate where the gross margin is 95% as large as the maximum payoff.

3. Empirical Case Study

Assessing whether a farmer is applying excess fertilizer (from an expected-profit perspective) requires information about the shape of the farmer's production function. Analysts have utilized a variety of functional forms, including quadratic, exponential, square root, linear-plus-plateau, and quadratic-plus-plateau (Shrader, Fuller and Cady, 1966; Cerrato and Blackmer, 1990;

[6] Provided that the optimal rate is not zero.

Bullock and Bullock, 1994; Overman, Wilson and Kamprath, 1994; Shapiro and Wortmann, 2006). Various studies comparing the performance of different functional forms for nitrogen fertilizer have identified the statistical superiority of forms that reach a plateau at high rates (Cerrato and Blackmer, 1990; Bullock and Bullock, 1994; Nyiraneza et al., 2010, Frank et al., 1990). For our primary results, we employ a negative exponential function, as preferred by Frank et al. (1990). To assess the robustness of our results, in an appendix we compare our empirical findings using alternative response functions, including quadratic plus plateau, linear-plus-plateau, and square-root-plus-plateau functions.

Yield response functions can vary greatly across space and over time (Mamo et al., 2003; Ruffo et al., 2006). To deal with this spatial and temporal variation in the responsiveness of crop yields to applications of N fertilizer, a range of approaches have been developed, including site-specific response functions (Hurley et al., 2004; Ruffo et al., 2006; Liu et al., 2006; Anselin et al., 2004), stochastic yield response functions (Boyer, 1982; Tembo et al., 2008) and mixed-effect hierarchical models (Wallach 1995; Ouedraogo and Brorsen, 2018). Compared with fixed parameter models, stochastic models allow the parameters to follow random distributions so one can make informed *ex ante* decisions about the optimal input use based on the distribution of potential outcomes.

3.1 Hierarchical Exponential Response Functions

We opted to use a hierarchical exponential variant of a payoff response function to incorporate site and year mixed effects that explicitly account for site and seasonal differences in the parameters of a fertilizer response function. Hierarchical models, also called multilevel models or mixed-effects models, consist of both fixed-effect and random-effect parameters to describe the population mean and the individual (site or seasonal) random variation around the population mean, respectively. Hierarchical models are commonly used for repeated measures or clustered observations (Lindstrom and Bates, 1990), which extends naturally to nitrogen response trials where correlations among observations collected at the same site have statistically significant consequences for estimated response function parameters using such data (Wallach, 1995).

Specifically, for site/season i, the relationship between observed crop yield Y_i and fertilizer rate N can be represented using the following hierarchical exponential model:

$$Y_i = a_i\big(1 - \exp\big(-b_i(c_i + N)\big)\big) + \varepsilon_i \tag{2}$$

where

$$\begin{aligned} a_i &= a_0 + \eta_a \\ b_i &= b_0 + \eta_b \\ c_i &= c_0 + \eta_c \end{aligned}$$

Here, the coefficients a_i, b_i, c_i have both fixed components (a_0, b_0, c_0) and random components (η_a, η_b, η_c). a_i is the intercept term representing crop yield at site/season i if no N fertilizer was applied, b_i is the slope parameter, and c_i is the curvature parameter. (η_a, η_b, η_c) represent the random effects following a joint normal distribution $N(0, \Omega)$ where Ω is a 3x3 variance-covariance matrix. ε_i is the idiosyncratic error following a normal distribution $N(0, \sigma_\varepsilon^2)$. We estimated our mixed-effects exponential models using the maximum likelihood algorithm proposed by Lindstrom and Bates (1990) implemented by the `nlme` function for non-linear mixed effect model estimation in the `nlme` package of R (Pinheiro and Bates, 2000).

Prices of input (fertilizer N) and output (corn) are important in farmers' decision making for achieving maximum farm profits. Specifically, for farmers facing fertilizer N price P_i^N and crop output price at P_i^Y (with the price ratio $R_i = P_i^N / P_i^Y$), their economically optimal N rate (EONR) solves the following profit maximizing problem:

$$\max_N \pi_i = P_i^Y Y_i - P_i^N N \quad (3)$$

The *ex post* EONR, assuming farmers know the response function parameters for that particular site/season, can then be solved as:

$$N_i^{EONR} = -\frac{1}{b}\ln\left(\frac{R_i}{ab}\right) - c \quad (4)$$

Facing variability in farm profits, farmers' risk attitudes also affect their input use decisions. Applying the expected utility framework and denoting farmers' utility for profit level π_i using function $u(\pi_i)$, we can derive the expected utility of farmers profit prospect as:

$$EU[\pi] = \sum_i \beta_i u(\pi_i) \quad (5)$$

where β_i is the probability of having profit level π_i. For specific utility functional forms, we adopt the widely used isoelastic utility function with constant relative risk aversion as follows:

$$u(\pi) = \frac{(w_0+\pi)^{1-\rho}}{1-\rho}, \text{for } \rho \geq 0, \rho \neq 1 \quad (6)$$

where w_0 is farmers' initial wealth and ρ is farmers' coefficient of relative risk aversion. Empirical measures of relative risk aversion typically reveal that most farmers are risk averse, but not highly so, with ρ ranging from between zero to about four in lower-income countries and somewhat less than four in high-income countries (Antle, 1987; Arrow, 1971; Bardsley and Harris, 1987; Binswanger, 1980; Bond and Wonder, 1980; Myers, 1989; Newbery and Stiglitz, 1981). Based on these findings, we set $\rho = 1.6$ for our base assumption, with sensitivity analysis using 0, 0.8, 1.6 and 3.2 reported in the Supplementary Materials. To derive the expected-profit-maximizing and utility-maximizing rates of N fertilizer, we applied a numerical method based on Monte Carlo simulation. First, we simulated 1,000 crop response functions based on random draws from the estimated parameter distributions in equation (2). We then calculated the corresponding profit-maximizing and utility-maximizing rates of N fertilizer using each of these simulated response functions. Based on information gleaned from MacDonald (2020) and USDA-ERS (2021), the representative farm size was set at 1,445 hectares with net farm household wealth totaling 2 million dollars (used as initial wealth w_0). The expected value and other statistics of the optimal N rates were calculated based on the simulation results.

3.2 Data

Yield response functions to nitrogen fertilizer are often estimated based on data from agronomic field experiments, where different amounts of N fertilizer are applied within a single site or across multiple sites, with a time span of one or multiple seasons. To explore the spatio-temporal variations in response functions, we used data on U.S. corn yield response to nitrogen application taken from two sources. One involved a single-site, multiple-season field experiment conducted on the Agricultural Engineering and Agronomy Research Farm near Ames, Iowa. The underlying experimental data were recovered from Puntel et al. (2016, Figure 1 and 2) using Engauge Digitizer (Mitchell et al., 2018). The continuous corn (CC) cropping system reported by Puntel (2016) included data for a total of 16 response curves representing the average corn yield under five N fertilizer rates (i.e., 0, 67, 134, 201, and 268 kg N ha^{-1}) for each of the years 1999 to 2014. The soybean-corn (SC) cropping system yielded a total of 15 average response curves for each of the years 2000 to 2014.

The second data source is a collection of response curves over multiple locations. For major U.S. corn-growing states in the mid-west region, sub-state, regional-level average response curves are reported by way of the online Corn Nitrogen Rate Calculator (Iowa State University Agronomy Extension and Outreach, 2018). This source provides regional-level recommendations regarding the economically optimal nitrogen application rate for corn farmers based on a set of fitted response curves. Six U.S. states (Illinois, Iowa, Michigan, Minnesota, Ohio, and Wisconsin) report sub-state, regional level average corn response curves derived from data collected from multiple sites within each of the regions. For our study, we obtained a total of 26 response curves representing different regions, soil types, irrigation and cropping systems (CC or SC) among these states. Images of the plotted response curves were digitized using Engauge Digitizer (Mitchell et al., 2018) to assess the variations in N response functions across location.

In addition to the N response data, determining the economically optimal N rate also requires data on the relative price of N fertilizer and corn. U.S. national average corn prices for each year 1960-2014 were taken from USDA-NASS (2018). We used the U.S. national average price of urea for each of the years during the period 1960-2014 reported by USDA-ERS (2018) to represent the price of N fertilizer. Nominal price levels were inflated or deflated to 2020 dollars using the U.S. GDP deflator. The relevant yearly ratios of N fertilizer to corn were derived using the corresponding input and output prices.

[Table 1: Summary statistics for corn and N-fertilizer prices in the U.S.]

As shown in Table 1, there was a large variation in both corn and N-fertilizer prices reported in the U.S. during 1960-2014, where the differences between minimum and maximum values reached 3.5-fold for N-fertilizer and 4.8-fold for corn. As a result, the price ratios between N-fertilizer and corn exhibited large year-to-year variations ranging from 0.0022 to 0.0101 with an average price ratio of 0.0058.

3.3 Results

Spatio-temporal Variation of EONR

Parameter estimates for the two data sources (single- vs multiple-sites) and two corn rotations—continuous corn (CC) versus soybean-corn (SC)—using the hierarchical exponential model, and alternative models (i.e., quadratic-plus-plateau, linear-plus-plateau, and square-root-plus-plateau) are reported in the Supplementary Materials Tables S1-S4. Based on our estimates of the hierarchical exponential response functions for the two data sources grouped by crop rotations, we plotted individual site/year specific gross margin functions (Figure 1). In Figure 1, the black dots represent the maximum gross margin for each payoff curve. For both the multiple-sites (Figure 1 right column) and the single-site (Figure 1 left column) estimates, there are large variations in both the corn yield response curves and the optimal N rates.

[Figure 1: Nitrogen payoff functions by crop rotation practices over different sites.]

Summary statistics for optimal N rates based on the distribution of the response function parameters and the historical price ratios are reported in Table 2. Between the two crop rotation systems, the SC rotation systems have lower average EONR than CC rotation systems (an average difference of 62 kg/ha for the single site case and 44 kg/ha for the multiple sites case), likely due to the availability of fixed nitrogen from the soybean crop in the subsequent corn crop. The standard deviations of the EONRs range from 44.6 kg/ha (for the CC rotation in single site) to 61.4 kg/ha (for the CC rotation in multiple sites), implying a wide range of optimal N rate choices by farmers across sites and between years.

[Table 2: Optimal N rate for different objectives]

Maximizing Expected Profits and Utility

In the previous section, profit-maximizing N rates were calculated separately for each year or location with fixed average price levels. In this section, we simulated 1,000 crop response functions first by randomly drawing parameters from the estimated parameter distributions. Then we randomly draw 1,000 price ratios based on the distribution of U.S. N-fertilizer and corn price ratios. Randomly drawn price ratios are applied to randomly simulated crop response functions to derive optimal N rates that maximize expected profit or expected utility. As shown in Figure 3, and reported in Table 2, the expected-profit-maximizing N rates range from 182 kg/ha (single-site, SC) to 242 kg/ha (single-site, CC), similar to the average of the individual optimal rates (Table 2). Relevant to risk-averse farmers, the spread of profits (shown as the distance between the 1st and 3rd quantile in the boxplots in Figure 2) gradually increases as the N fertilizer application rate increases, indicating that applying more N results in greater risk. However, within the vicinity of the optimal N rate, the marginal increase in risk is very slight. For risk-averse farmers (with relative risk aversion of 1.6), their expected utility maximizing N rates are almost identical to the risk-neutral case (within 0.01% difference) (Table 2), indicating that farmers' risk attitudes should not be a significant factor in determining their N rate choices. (See Supplementary Material Table S7 for robustness checks using risk aversion parameters ranging between 0.0 and 3.2.)

[Figure 2: Distribution of profits under different N fertilizer rate]

[Figure 3: Expected profits under different N fertilizer rate]

Flatness in Payoff Functions

In Figures 1 and 3, the black lines illustrate the flat regions below the optimum N rate that result in at least 95% of the maximum gross margin. The impact of reducing N compared with their economically optimum level (EONR) on profit level differs depending on each specific payoff function. The relatively flat region below EONR means that it is possible to reduce N rates by 42 to 52% without reducing gross margin by more than 5% (Table 3). The flatness in gross margins around the optimal N rates are also illustrated in Figure 4, where farmers can substantially reduce N use—by approximately 40-50% from their optimal level—and still achieve at least 95% of their optimal gross margin. Moreover, a still sizable 10% to 20% reduction in N rate results in a very modest 0.1% to 0.9% profit loss on average. Soybean-corn rotations have wider flat regions compared with continuous corn rotations, so farmers who rotate corn crops with soybean crops can reduce N rate in their corn crops even further without much profit loss compared with farmers who are continuously cropping corn.

[Table 3: Flat regions below the optimal N rate]
[Figure 4: Flatness of profits in response to reduction in N rate]

4. Policy Options to Mitigate Water Pollution

We have identified three factors that create opportunities to reduce the public costs of nitrogen pollution from agriculture at relatively low private or public cost.[7] A key question is how various policy mechanisms might be used to exploit these three factors most effectively. We now discuss a number of policy options.

4.1 Pricing Nitrogen Externalities

One obvious option is to impose a pollution tax on the quantity of N that leaves the farm boundary (e.g., Bryant and Goldman-Carter, 2016; Shr and Zhang, 2021) or, more simply, on each unit of N fertilizer applied. To our knowledge, this polluter-pays approach has not been

[7] For additional discussion of these and other mitigation options see OECD (2017), Pannell et al. (2020) and Sud (2020, especially Table 4.1).

applied to N fertilizer in agriculture, perhaps because of the size of the tax needed to achieve pollution-reduction targets. Based on our analysis of corn in the U.S. presented above, achieving a 20% reduction in N rates would require a 100% tax on N fertilizer (Figure 5). The tax required for a 30% reduction would be substantially more onerous again: a three- to four-fold increase in the average price ratio relative to the average of our data (Figure 5). Even the substantial spike in fertilizer prices observed in 2021 (Widmar, 2021) did not reach these levels. If such a large change in price ratio was achieve by a permanent pollution tax on N fertilizer, the consequences for farm profits would be substantial, so this approach seems unlikely to be politically viable in most countries.

[Figure 5: Sensitivity of optimal N rate in response to N price increase]

A cap-and-trade scheme with grandfathered permits could potentially achieve the same price incentive without imposing such a large total cost on farmers but, to our knowledge, even this approach has not been utilized to achieve fertilizer rate reductions, except as offsets for emission increases by other polluters.

4.2 Incentive Payments

As noted above, the flatness of the profit function means that the cost of fully compensating farmers for reducing their nitrogen rates below privately optimal levels would be relatively low. This means that payments to incentivize farmers to voluntarily reduce their rates could be a cost-effective policy mechanism. For example, based on our case-study results, the cost of fully compensating farmers for reducing N rates by 20% below profit maximizing rates would be $14 to $21 per acre on average. This is substantially less than payments currently offered under existing programs for some other actions. For example, under the EQIP program in 2019, farmers who planted cover crops[8] could receive payments for planting cover crops averaging $43 per acre at the basic level, $50 per acre for multi-species plantings, or $63 per acre at the highest rate (Myers et al., 2019). Even with these payments available, adoption of cover crops has been low–around 5 percent of harvested cropland (net of alfalfa acreage) in 2017 (Wallander et al., 2021)–suggesting that the net cost of cover crop adoption for most farmers is higher than these payment levels. Incentivizing behavior change would probably require payment levels that more than compensate for opportunity costs.

4.3 N Rate Reduction Insurance

Given that farmers are likely to be uncertain about the consequences of reducing N rates, it may be possible to design insurance products that contribute to reducing fertilizer usage. One existing insurance option encourages splitting of N application into two or more applications, rather than applying all the nitrogen at seeding time (see USDA-RMA, 2022a). The environmental benefit from splitting is that N supply can be better matched with crops' demand depending on weather during the growing season, reducing the risk of over-supply leading to N losses. A risk of the approach for farmers is that they may be unable to make a second fertilizer application that would have been beneficial, due to the field being too wet to allow vehicle passage without bogging (Gramig et al., 2017). The Post Application Coverage Endorsement (PACE) enabled by the new USDA-RMA program provides payments for the projected yield lost in that situation, removing a disincentive for rate splitting (USDA-RMA 2022b).

Our evidence presented above suggests that a different type of insurance should also be considered: one that compensates farmers for profit reductions resulting from cutting N rates in

[8] In a comprehensive review of the literature, Justes (2017) concluded that cover crops reduce the leaching of nitrates into aquifers by 20 to 90%, depending on the situation.

general, rather than specifically from rate splitting. Such an approach has been discussed and piloted previously. Thorburn et al. (2020) assessed the potential for such a scheme to be commercially viable in the context of sugar farms in Queensland, Australia, adjacent to the Great Barrier Reef. They concluded that "… insuring against the risk of sugarcane yield loss with reduced N fertilizer applications is technically feasible" (Thorburn et al., 2020, p.2) but that more work was needed to establish its commercial viability. Agflex Inc. (2011) reported the results of a pilot scheme called the BMP Challenge, which provided foregone income and technical assistance to corn growers in 12 U.S. states who reduced their N rates. They concluded that "The BMP Challenge is cost effective, reducing nitrogen losses at an average cost of $1.87 per pound, comparable to or below the cost of alternative practices" (Agflex Inc., 2011, p.3). They noted that changes to the scheme could reduce the cost still further. The two studies utilized different methods for estimating the degree of income loss: simulation modelling (Thorburn et al., 2020) and placement of a control strip within the field where farmers implement their conventional practice (Agflex Inc., 2011). They also varied in the intended source of revenue for meeting claims: participants' premiums in a commercial service (Thorburn et al., 2020) or an external funder seeking public benefits (Agflex Inc., 2011). Agflex Inc. (2011) observed that many farmers stated their intention to continue to use reduced rates after the program. This suggests that a strong focus on scientific and economic evidence had improved farmers' understanding about the effects of nitrogen fertilizer on yield, profit and risk.

Palm-Forster et al. (2017) found that farmers were less attracted to BMP insurance (i.e., protection against yield loss from BMP use) than to some other policy mechanisms "due to uncertainty about how the program will be implemented and the reliability of indemnities, as well as anticipated transaction costs associated with the program" (Palm-Forster et al., 2017, p.

493). This would need to be considered in the specific design of a scheme for large-scale implementation. Nevertheless, the three factors we have focused on (over-application, increasing risk and flat payoff functions) provide encouraging signs that this approach may be worth exploring further.

4.4 Regulation

Policy makers have the option of applying command-and-control regulation. For example, Australian farmers in the Great Barrier Reef catchment are regulated to comply with a fertilizer plan that avoids over-application[9]. Since 2006, Dutch farmers have been subject to fertilizer (N and P) application standards that include limits on the amount, type and timing of fertilizer applications (Schröder and Neeteson, 2008; Van Grinsven et al., 2016). The three production economics factors discussed here mean that the cost of compliance will be low, making a regulatory approach to reducing fertilizer rates less politically challenging than it would otherwise be.

4.5 Information and Persuasion

Finally, there is scope for information-based policy mechanisms to utilize any or all of the three factors identified above. Traditional extension approaches providing information about the effects of N rate cuts on yields, profit, and risk would likely convince some farmers. Other farmers may respond more to participatory extension approaches involving on-farm demonstrations, farmer-group discussions, farmer-driven trials, and so on. The tools and approaches of behavioral economics (Streletskaya et al., 2020) could be employed to develop

[9] https://www.qld.gov.au/environment/agriculture/sustainable-farming/reef/reef-regulations/producers/sugarcane [Accessed April 4, 2022].

interventions that build on the production-economics results presented here. These approaches could be combined with the incentive-based or regulatory mechanisms discussed above.

We anticipate that information-based or suasive approaches are likely to be most effective in situations where there is a private net benefit from the practice being promoted (as well as a public benefit). This suggests that farmers who apply N fertilizer at rates above their economic optimum could be the main targets for these approaches.

On the other hand, the existence of flat payoff functions means that the private net benefits from reducing rates (increased profit and reduced risk) will probably be small, providing little incentive for behavior change. For that reason, appeals to farmers' public spiritedness (Chouinard et al., 2008) may assist to motivate change. For those farmers who do not over-apply N, public benefits are the only potential driver of a persuasive strategy. For example, this might include an emphasis that farmers' last 50 lb/acre of nitrogen makes them almost no profit but has relatively high public costs because marginal losses of nitrogen are highest at high fertilizer rates, meaning that a large proportion of the marginal nutrients end up in water bodies. For those farmers whose drinking water comes from groundwater on their property, there could be an additional element of self-interest. Reducing N rates could reduce the risk of health impacts on themselves or their families (Ward et al., 2018), or at least reduce the need for costly water treatment (see, e.g., Rahimia et al., 2020).

Finally, we note that, on an increasing number of farms, the use of variable rate (application) technologies are enabling farmers to have more control over the amount, timing and within-field placement of fertilizers (see, e.g., Finger et al., 2019). This relatively new technology may provide a vehicle for practical field-level implementation of new policies that aim to reduce overall usage of nitrogen fertilizers.

5. Conclusion

Of the various methods available for reducing nitrogen pollution in water bodies sourced from agricultural fertilizers, reducing farmers' application rates for nitrogen fertilizers appears likely to be among the most efficient approaches. We have presented three empirical results from the production economics of nitrogen fertilizer that appear to offer untapped potential for efficient policies to reduce nitrogen application rates. These are that, a) many farmers apply higher rates of N fertilizer than would maximize their own private interests, b) N fertilizer is a not risk-reducing input, and c) the relationship between N rate and profit is usually flat over a wide range of N rates. Of these three insights, the first is widely recognized but the second and third are not. Indeed, we anticipate that many farmers and some farm advisers will need convincing that they are true. Fortunately, there is overwhelming empirical evidence to back these three insights up.

Each of the three insights has potential to facilitate policies of various types. They mean that policy costs would be relatively low and effectiveness relatively high, compared with situations where the empirical results were otherwise. This is true for both traditional policy approaches (agricultural extension, incentive payments) and relatively novel ones (insurance to compensate for economic losses, behavioral economics). We would like to see greater experimentation with policy approaches that exploit these insights derived from production economics.

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Tables and Figures

Table 1. Summary statistics for corn and N-fertilizer prices in the U.S.

Variable	Mean	SD	Min	Median	Max
Corn price ($/metric ton)	223.23	86.94	102.29	212.15	494.61
N-fertilizer price ($/kilogram)	1.21	0.38	0.63	1.14	2.23
Price ratio: N/Corn	0.0058	0.0015	0.0022	0.0056	0.0101

Note: Yearly corn prices during 1960-2014 for the U.S. are collected from USDA-NASS (2018). Urea prices during 1960-2014 for the U.S. are collected from USDA-ERS (2018). Nominal corn prices and nominal urea prices are converted to the 2020 US dollars using the US GDP deflator from the World Bank.

Table 1. Optimal N rate for different objectives

Cropping system	Data source	Average Economically Optimum N Rate	Expected Profit Maximizing N Rate	Expected Utility Maximizing N Rate	Certainty Equivalent N Rate
		(kg/ha)	*(kg/ha)*	*(kg/ha)*	*(kg/ha)*
Continuous Corn (CC)	**Single site**	244 (44.56)	242	242	239
	Multiple sites	240 (61.44)	237	237	234
Soybean Corn (SC)	**Single site**	182 (45.38)	182	182	179
	Multiple sites	196 (48.25)	195	195	192

Note: Standard deviations are in parenthesis. Relative risk aversion parameter was set at 1.6 when calculating the "Expected Utility Maximizing N Rate" and the "Certainty Equivalent N Rate". Results for additional risk aversion parameters were included in Supplementary Material Table S7.
Source: developed by authors.

Table 3. Flat regions below the optimal N rate

Cropping System	Data source	Average flat region as a share of optimal N rate
Continuous Corn (CC)	**Single site**	0.42 (0.03)
	Multiple sites	0.44 (0.04)
Soybean Corn (SC)	**Single site**	0.52 (0.05)
	Multiple sites	0.50 (0.05)

Note: Flat region is measured as the proportional reduction in N rate that can be made without reducing gross margin by more than 5% below the optimum. Standard deviations are in parenthesis.
Source: developed by authors

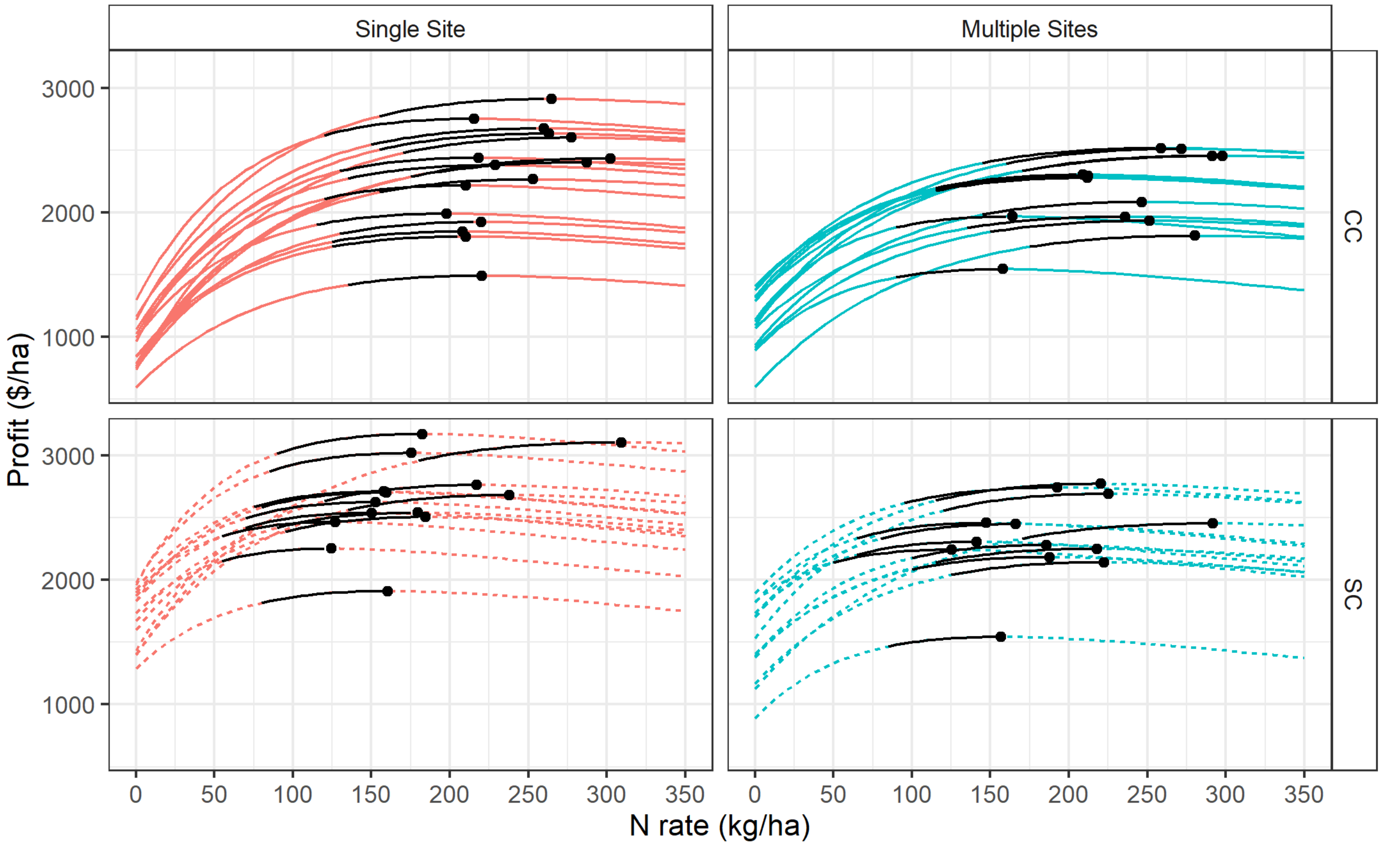

Figure 1. Nitrogen payoff functions across different cropping systems over different sites.

Note: Black dots represent the economically optimum Nitrogen rate (EONR) for each nitrogen payoff function and black lines illustrate the flat regions within 95% of the optimal profit, evaluated at average corn and nitrogen price levels. CC is a continuous corn rotation and SC is a soy-corn rotation.
Source: These response curves were estimated using two different data sources: (1) single-site, multiple-season field experimental data for both CC and SC rotations were recovered from Puntel et al. (2016); (2) multiple-sites crop response curves for both CC and SC rotations were recovered from the online Corn Nitrogen Rate Calculator (Iowa State University Agronomy Extension and Outreach, 2018).

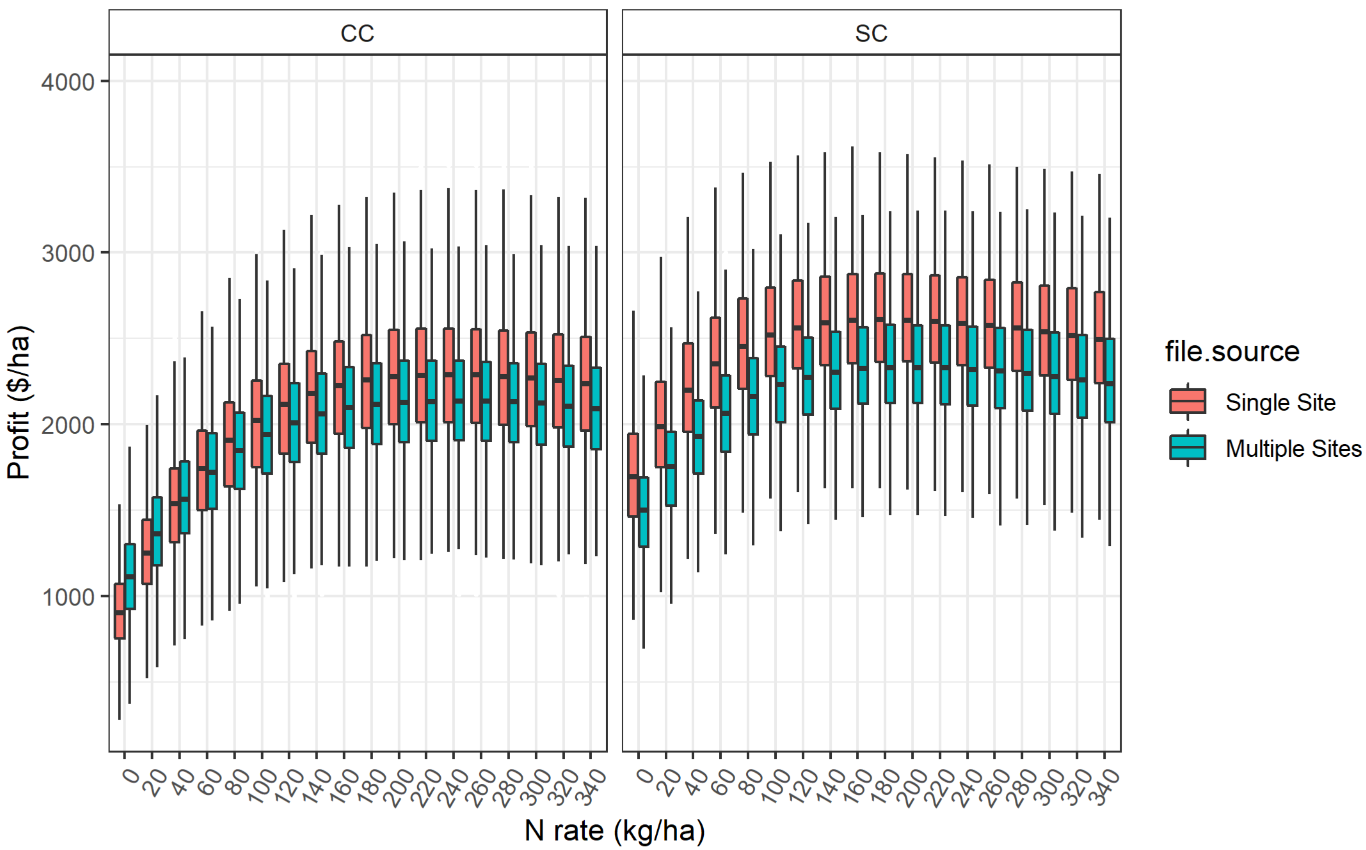

Figure 2. Distribution of profits under different N fertilizer rate.

Note: Two cropping systems from two data sources are illustrated here: the continuous corn (CC) system (left panel) and soybean corn (SC) rotation system (right panel), using both single-site (Puntel et al. 2016, red color) and multiple-sites (Corn Nitrogen Rate Calculator 2018, blue color) data. For the box plot, the lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles) with the middle line corresponds to the median from the distribution of simulated profits under different N rates. The upper (lower) whiskers extend from the upper (lower) hinge to the largest (smallest) value no further than 1.5 times of the inter-quartile range (distance between the first and third quartiles). Outliers were omitted in this figure.
Source: developed by authors

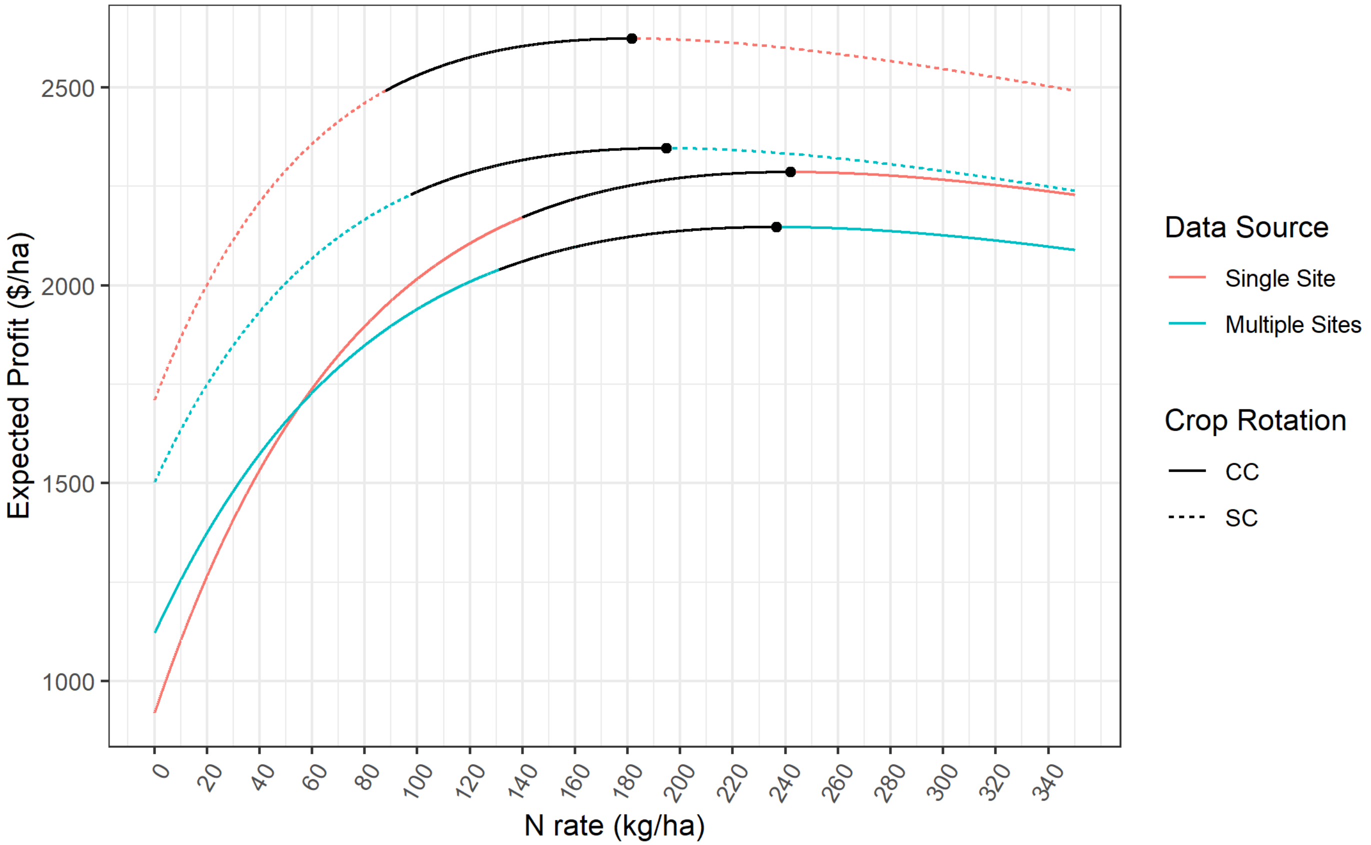

Figure 3. Expected profits under different N fertilizer rate.

Note: Two cropping systems from two data sources are illustrated here: continuous corn (CC, solid line) and soybean-corn (SC, dashed line) crop rotations for either a single-site (red) or multiple-sites (blue). The black dots represent the expected profit maximizing N rate for each expected profit curve. The black lines represent the flat region under the optimal N rate where at least 95% of the maximum expected profits are achieved.
Source: developed by authors

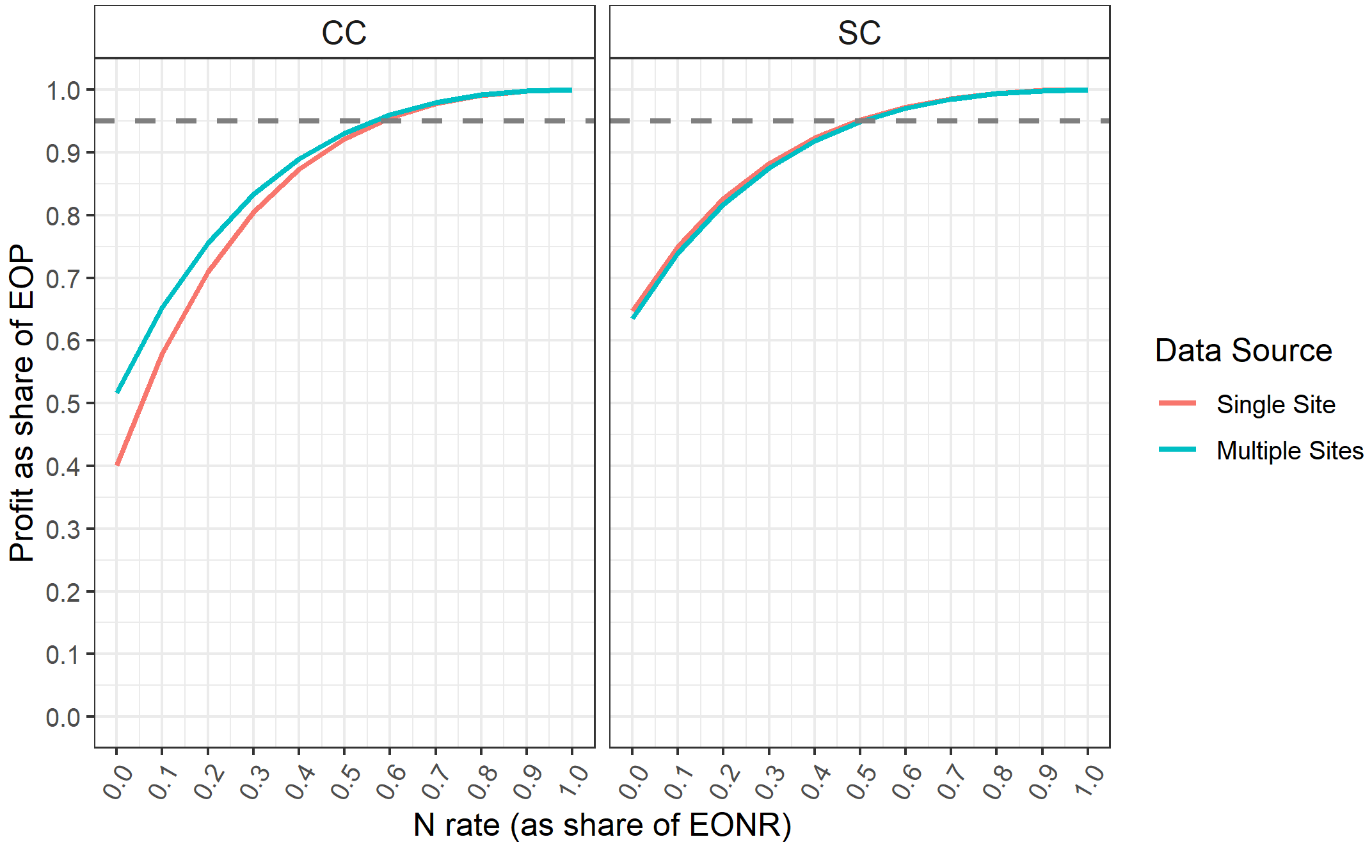

Figure 4. Flatness of profits in response to reduction in N rate.

Note: The x-axis measure reduction in N rate (as share of the EONR) and y-axis measures the reduction in profits (as share of the economically optimum profits).
Source: developed by authors

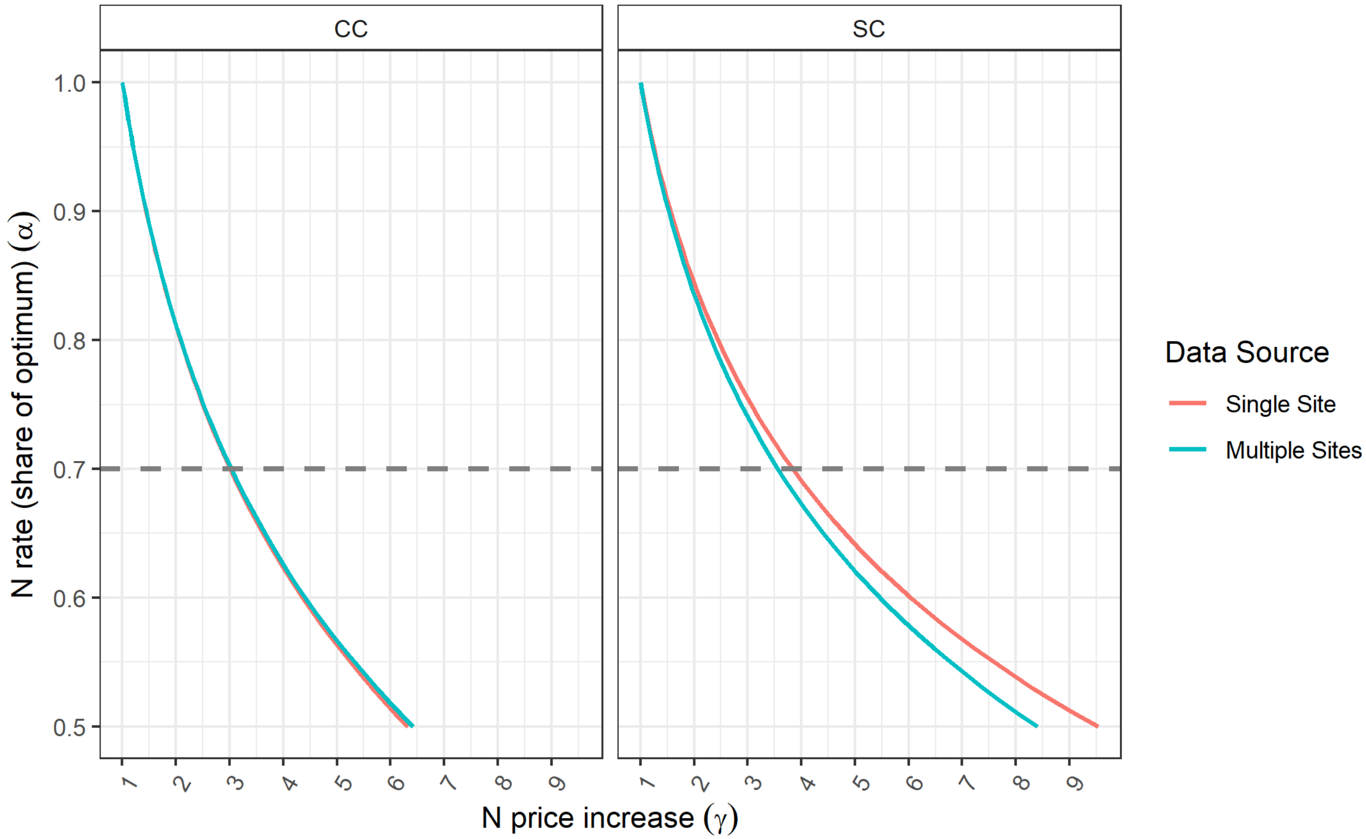

Figure 5. Sensitivity of optimal N rate in response to N price increase.

Note: The x-axis represents the increase in N fertilizer price (e.g., γ-fold of the 2018 price level) and y-axis measures the reduction in optimal N rate compared to the profit-maximizing N rate at the original price level.
Source: developed by authors.

Supplementary Material

Alternative models for crop response to nitrogen fertilizer application

In addition to the exponential models presented in the main paper, we also estimated several different response models to compare their results and investigate the effect of model selections on N fertilizer decision making. Three additional response models were fit to the data from both the single-site and multiple sites with either continuous corn (CC) or soybean-corn (SC) crop rotation systems. Specifically, the relationship between observed crop yield Y_i at site/year i and fertilizer rate N are modeled using quadratic-plus-plateau, linear-plus-plateau, square-root, and exponential models.

The quadratic-plus-plateau model can be represented as:

$$Y_i = \begin{cases} a_i + b_i N + c_i N^2 + \varepsilon_i & \text{if } N \leq -b_i/2c_i \\ Y_i^{Max} & \text{if } N > -b_i/2c_i \end{cases}$$

The mixed-effect linear-plus-plateau model can be represented as:

$$Y_i = \begin{cases} a_i + b_i N + \varepsilon_i & \text{if } N \leq c_i \\ a_i + b_i\, c_i & \text{if } N > c_i \end{cases}$$

The mixed-effect square-root model can be represented as

$$Y_i = a_i + b_i N + c_i \sqrt{N} + \varepsilon_i$$

The mixed-effect exponential model can be represented as

$$Y_i = a_i\big(1 - \exp\big(-b_i(c_i + N)\big)\big)$$

For each of the above models, we have

$$\begin{aligned} a_i &= a_0 + \eta_a \\ b_i &= b_0 + \eta_b \\ c_i &= c_0 + \eta_c \end{aligned}$$

where the coefficients have both a fixed and random component. All mix-effects models are estimated using the `nlme` function for non-linear mixed effect model estimation in the `nlme` package of R.

Estimation Results

Parameter estimations for alternative response models are reported in **Table S1-S4** for the four sets of yield response data used in the main paper. For all models, the fixed effect parameter estimates are significant at the 1% probability level. For the random effects, the parameter standard deviations from the multiple-sites (i.e., Corn Nitrogen Rate Calculator website) are higher than the estimates derived from the single-site (Puntel et al. 2016) data. Based on the AIC and BIC criteria, quadratic-plus-plateau model and exponential model are preferred over linear-plus-plateau or square-root models.

Economically Optimum N Rate and Flat Payoff Functions

The choices of models can affect the decisions on economically optimum N rate as well as the flatness of the payoff functions. In practice, the EONR is derived by taking the first-order-condition of the payoff functions, so the curvature of these different models can affect the EONR choice. As shown in Table S5, linear-plus-plateau models have the lowest average EONR, followed by the quadratic-plus-plateau models. Exponential and square-root models in general have much higher average EONR levels. Furthermore, the different curvatures of these alternative models also result in different share of the 95% optimal payoff flat region (Table S6), where linear-plus-plateau model has the narrowest flat region, followed by quadratic-plus-plateau model, where exponential and square-root models have much wider flat regions.

Table S1. Alternative model comparisons for the estimation of corn yield response to N fertilizer under the continuous corn crop system within single-site over multiple years

Data source	**Single-site over multiple years under continuous corn (CC) system**			
Models	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root-plus-plateau**	**Exponential**
Parameters				
Fixed effect				
a_0	4.21***	4.27***	4.12***	12.17***
	(0.26)	(0.27)	(0.28)	*(0.51)*
b_0	0.072***	0.056***	-0.010***	0.012***
	(0.0042)	(0.0027)	(0.0027)	*(0.00086)*
c_0	$-1.8\text{x}10^{-4}$***	127.56***	0.64***	35.73***
	($1.8x10^{-5}$)	(6.824)	(0.048)	*(3.02)*
Random effect				
σ_{η_a}	0.96	0.95	0.88	1.88
σ_{η_b}	0.014	0.0072	0.0028	0.0019
σ_{η_c}	$5.8\text{x}10^{-5}$	22.90	0.081	6.71
$cor(a,b)$	-0.18	-0.24	0.233	-0.22
$cor(a,c)$	0.19	0.063	-0.329	0.16
$cor(b,c)$	-0.89	-0.30	-0.833	-0.57
Log-likelihood	-93.75	-106.77	-109.82	-99.17
AIC	207.50	227.54	233.63	212.35
BIC	231.32	244.21	250.31	229.02

Note: standard deviations are in parenthesis.
*** Significant at p=0.01; ** significant at p=0.05; * significant at p=0.10.
Source: developed by authors

Table S2. Alternative model comparisons for the estimation of corn yield response to N fertilizer under the soybean-corn crop system within single-site over multiple years

Data source	**Single-site over multiple years under soybean-corn (SC) system**			
Models	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root**	**Exponential**
Parameters				
Fixed effect				
a_0	7.69***	7.64***	7.63***	13.26***
	(0.27)	(0.29)	(0.30)	*(0.46)*
b_0	0.061***	0.051***	-0.013***	0.015***
	(0.0041)	(0.0035)	(0.0022)	*(0.0013)*
c_0	$-1.8\text{x}10^{-4}$***	101.26***	0.54***	57.51***
	($1.8x10^{-5}$)	(6.53)	(0.039)	*(3.97)*
Random effect				
σ_{η_a}	0.95	0.96	1.01	1.66
σ_{η_b}	0.012	0.0095	0.0036	0.0033
σ_{η_c}	$4.7\text{x}10^{-5}$	19.80	0.085	7.53
$cor(a,b)$	0.091	-0.186	0.14	-0.11
$cor(a,c)$	-0.47	0.058	-0.19	0.11
$cor(b,c)$	-0.79	-0.302	-0.69	-0.56
Log-likelihood	-73.45	-83.68	-80.84	-73.82
AIC	166.90	181.36	175.68	161.65
BIC	189.38	197.10	191.42	177.39

Note: standard deviations are in parenthesis.
*** Significant at p=0.01; ** significant at p=0.05; * significant at p=0.10.

Source: developed by authors

Table S3. Alternative model comparisons for the estimation of corn yield response to N fertilizer under the continuous corn crop system across multiple sites

Data source	**Multiple-sites under continuous-corn (CC) system**			
Models	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root-plus-plateau**	**Exponential**
Parameters				
Fixed effect				
a_0	5.22***	5.57***	4.13***	11.60***
	(0.28)	(0.29)	(0.30)	(0.42)
b_0	0.052***	0.036***	-0.0091***	0.011***
	(0.0015)	(0.00080)	(0.0014)	(0.00069)
c_0	$-1.2\text{x}10^{-4}$***	145.45***	0.59***	53.29***
	$(6.5\text{x}10^{-6})$	(5.23)	(0.019)	(3.12)
Random effect				
σ_{η_a}	1.02	1.02	1.03	1.52
σ_{η_b}	0.0054	0.0024	0.0037	0.0024
σ_{η_c}	$2.3\text{x}10^{-5}$	18.29	0.031	10.91
$cor(a,b)$	-0.009	-0.054	0.132	-0.009
$cor(a,c)$	-0.023	0.011	-0.207	0.010
$cor(b,c)$	-0.583	-0.090	-0.559	-0.037
Log-likelihood	385.18	-67.77	-123.07	156.48
AIC	-756.35	149.54	260.14	-298.96
BIC	-718.51	176.03	286.62	-272.47

Note: standard deviations are in parenthesis.
*** Significant at p=0.01; ** significant at p=0.05; * significant at p=0.10.

Source: developed by authors

Table S4. Alternative model comparisons for the estimation of corn yield response to N fertilizer under the soybean-corn crop system across multiple sites

Data source	**Multiple-sites under soybean-corn (SC) system**			
Models	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root-plus-plateau**	**Exponential**
Parameters				
Fixed effect				
a_0	6.98***	7.27***	5.96***	12.06***
	(0.38)	(0.36)	(0.39)	*(0.42)*
b_0	0.049***	0.033***	-0.013***	0.013***
	(0.0019)	(0.0011)	(0.0011)	*(0.00074)*
c_0	$-1.3\text{x}10^{-4}$***	127.57***	0.57***	62.43***
	($4.3x10^{-6}$)	(5.38)	(0.024)	*(2.72)*
Random effect				
σ_{η_a}	1.35	1.30	1.39	1.52
σ_{η_b}	$6.5\text{x}10^{-3}$	0.0038	0.0028	0.0026
σ_{η_c}	$1.5\text{x}10^{-5}$	18.91	0.067	9.39
$cor(a, b)$	-0.266	-0.028	0.092	-0.005
$cor(a, c)$	-0.112	0.007	-0.092	0.006
$cor(b, c)$	-0.450	-0.063	-0.418	-0.051
Log-likelihood	360.47	-26.60	-83.69	218.46
AIC	-700.95	67.20	181.38	-422.92
BIC	-663.11	93.69	207.86	-396.44

Note: standard deviations are in parenthesis.
*** Significant at p=0.01; ** significant at p=0.05; * significant at p=0.10.

Source: developed by authors

Table S5. Distribution of Economically Optimum N Rate for alternative models

		Economically Optimum N Rate (kg/ha)			
Cropping system	**Data source**	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root-plus-plateau**	**Exponential**
Continuous Corn (CC)	**Single site**	196.81	127.00	298.45	243.78
		(62.45)	(23.42)	(39.33)	(44.56)
	Multiple sites	190.61	145.47	269.09	240.43
		(32.71)	(18.25)	(50.04)	(61.44)
Soybean Corn (SC)	**Single site**	160.20	101.63	225.71	182.00
		(51.19)	(19.76)	(58.57)	(45.38)
	Multiple sites	167.75	126.72	242.93	196.01
		(27.51)	(18.86)	(57.00)	(48.25)

Note: standard deviations are in parenthesis. For the "quadratic-plus-plateau" and "square-root-plus-plateau" models, parameter simulations were restricted to be within the minimum and maximum parameter range based estimated individual site/year parameters to avoid unrealistic extreme values.
Source: developed by authors

Table S6. Flat regions below the optimal N rate which yield at least 95% of the optimal level profits for alternative models

		Flat region below optimal N (as a share of optimal N rate)			
Cropping system	**Data source**	**Quadratic-plus-plateau**	**Linear-plus-plateau**	**Square-root-plus-plateau**	**Exponential**
Continuous Corn (CC)	**Single site**	0.29 (0.027)	0.18 (0.033)	0.51 (0.020)	0.42 (0.026)
	Multiple sites	0.33 (0.025)	0.26 (0.044)	0.51 (0.022)	0.44 (0.039)
Soybean Corn (SC)	**Single site**	0.38 (0.065)	0.24 (0.052)	0.62 (0.033)	0.51 (0.049)
	Multiple sites	0.38 (0.047)	0.30 (0.056)	0.57 (0.035)	0.50 (0.047)

Note: standard deviations are in parenthesis.
Source: developed by authors

Table S7. Expected utility maximizing N rate under different risk aversion assumptions

Cropping system	**Data source**	**Expected Utility Maximizing N Rate under different risk aversion**			
		$\boldsymbol{\rho = 0}$ *(kg/ha)*	$\boldsymbol{\rho = 0.8}$ *(kg/ha)*	$\boldsymbol{\rho = 1.6}$ *(kg/ha)*	$\boldsymbol{\rho = 3.2}$ *(kg/ha)*
Continuous Corn (CC)	**Single site**	241.98	241.98	241.98	241.98
	Multiple sites	236.65	236.65	236.65	236.65
Soybean Corn (SC)	**Single site**	181.72	181.72	181.72	181.71
	Multiple sites	194.77	194.77	194.77	194.77