

A Nonlinear Offset Program to Reduce Nitrous Oxide Emissions Induced by Excessive Nitrogen Application

Francisco Rosas, Bruce A. Babcock, and Dermot J. Hayes

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**Center for Agricultural and Rural Development
Iowa State University
Ames, Iowa 50011-1070
www.card.iastate.edu**

Francisco Rosas is a PhD candidate and research assistant in the Department of Economics and Center for Agricultural and Rural Development (CARD) at Iowa State University. Bruce Babcock and Dermot Hayes are professors in the Department of Economics and in CARD.

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Questions or comments about the contents of this paper should be directed to Dermot Hayes, Iowa State University, 568C Heady Hall, Ames, Iowa 50011-1070; Ph: (515) 294-6185; Fax: (515) 294-6336; E-mail: dhayes@iastate.edu.

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Abstract

On average, U.S. farmers choose to apply nitrogen fertilizer at a rate that exceeds the expected agronomically optimal rate. The technology underlying the yield response to nitrogen rewards producers who over apply in years when rainfall is excessive. The overapplication of nutrients has negative environmental consequences because the nitrogen that is not taken up by the plant will typically volatilize causing N₂O emissions, or leach causing water pollution. We present a nonlinear offset program that induces farmers to reduce their nitrogen applications to the level that will be consumed by the plant in a typical year and, as a result, reduce N₂O emissions from agriculture. The offset program is nonlinear because of the nonlinear relationship between N₂O and nitrogen application rates. We assume that the farmer solves an expected utility maximization problem, choosing the optimal nitrogen application rate. The key contribution is a set of simulations that shows that modest offset payments will induce participation in the program and will have a significant impact on both expected and actual N₂O emissions without having a significant impact on actual or expected yields. We also find that more risk-averse farmers will reduce emissions by a greater amount than less risk-averse farmers. Finally, we show the distribution of emission reductions induced by this nonlinear offset scheme.

Keywords: carbon offsets, nitrogen fertilizer, nitrous oxide, pollution, uncertainty.

JEL Codes: Q12, Q18, Q51, Q53, Q54, D8

A Nonlinear Offset Program to Reduce Nitrous Oxide Emissions Induced by Excessive Nitrogen Application

The nitrogen (N) fertilizer application decision is made under uncertainty because the N available to the crop during the growing season is affected by weather conditions (especially rainfall and temperature). Also, there is evidence in the literature that, ex post and on average, U.S. farmers apply more N fertilizer than the agronomic optimum. The reason behind this behavior is the Leontief-like technology underlying the response of yields to both N fertilizer and weather conditions. This technology is such that the nutrient provided in the smallest amount becomes the limiting nutrient. This gives farmers the incentive to apply more N fertilizer expecting the growing season to be either wet or warm. However, evidence in the literature suggests that this overapplication of nutrients is ex ante optimal (Babcock 1992; Sheriff 2005).

The overapplication of N has environmental effects, such as volatilization of N_2O , water pollution, and other indirect effects on human health (Townsend et al. 2003; Galloway et al. 2008). We focus here on nitrous oxide (N_2O), a greenhouse gas (GHG) with global warming potential (GWP) 310 times higher than that of carbon dioxide (CO_2) over a 100-year time period.

Several studies using calibrated N_2O emissions models (Maggi et al. 2008; Del Grosso et al. 2006; Grant et al. 2006; and Li, Narayanan, and Harriss 1996), field experiment data (Hoben et al. 2011; Chen, Huang, and Zou 2008; McSwiney and Robertson 2005; Chantigny et al. 1998; Izaurralde et al. 2004; and Yamulki et al. 1995), thorough literature reviews of peer-reviewed studies (Snyder et al. 2009; and Bouwman, Boumans, and Batjes 2002), or conceptual models of N input saturation on ecosystems (Townsend et al. 2003) have documented that low N_2O emissions occur when N is

applied at or below the optimal crop requirement, but that higher emissions are consistent with N rates greater than that threshold. This literature suggests that crops compete with N₂O-producing microbes for the use of N in soil, limiting N₂O production until crop N uptake has been satisfied. If the crop uses all available N in the soil, N₂O emissions will be low. Emissions will increase rapidly once the crop's N demand is satisfied.

Consequently, a nonlinear relationship between N₂O emissions and the N application rate is appropriate. For illustration, figure 1 shows the results of a literature review conducted by Bouwman, Boumans, and Batjes (2002) of more than 900 measures of N₂O emissions from peer-reviewed studies for different types and rates of fertilizer, crops, soil types/qualities, and lengths of experiments. The literature is not conclusive as to whether emissions increase at an increasing or decreasing rate once the crop N requirement has been passed.

The response of yields to increasing nitrogen application has also been widely documented in the literature. Different functional forms have been employed to describe this relationship (quadratic, linear response and plateau, quadratic response and plateau, and Mitscherlich, among others). Berck and Helfand (1990) and Tembo et al. (2008) provide thorough overviews and discussions about the different production functions estimated in the literature. Most of these studies have also considered the stochastic nature of agricultural production due to uncertain weather, pests, and soil qualities.

The nonpoint source (NPS) nature of N₂O emissions implies that the most effective way to address the environmental consequences is by altering the use of the input that ultimately causes the pollution (Hansen 1998; Shortle and Abler 1997; Xepapadeas 1997; and Segerson 1988). In this article we present the magnitudes of the economic tradeoffs

involved in reducing N₂O emissions by cutting N fertilizer applications for different CO₂ prices. The yield and N₂O response curves are estimated using field-level data. The curves are used to estimate the magnitude of the N₂O reductions that are economically sensible given the value of N in crop production relative to the value of cutting N to control N₂O emissions.

Optimization under an Offset Program

Suppose there exists a representative farmer who maximizes expected utility of per hectare profits by choosing the optimal level of N fertilizer application rate (in kilograms per hectare); so the farmer's problem is $\max_{[N]} EU(\tilde{\pi}) = \max_{[N]} EU(\tilde{P}\tilde{y}(N) - P_N N)$, where $U(\cdot)$ is a strictly increasing and concave utility function, \tilde{P} is the unknown output price at harvest time, $\tilde{y}(N)$ is the concave yield response function affected by random weather during the growing season, and P_N is the observed price of the fertilizer input. Expectations (E) are taken over the two random variables. Assuming, to facilitate the exposition, that $U(\cdot)$ is linear (i.e., risk neutrality) and that yield and output prices are independent random variables,¹ and denoting expected values with a bar, the first-order condition (FOC) is $\bar{P} \frac{\partial \bar{y}(N)}{\partial N} = P_N$. We denote its optimal solution as \bar{N} . Panel (a) of figure 2 shows the expected N₂O emissions associated with the optimal fertilizer application, and panel (b) shows the optimal \bar{N} at the intersection between the decreasing expected marginal value product curve and the constant observed marginal cost P_N (point A).

Now suppose that society assigns a value to the environmental damage caused by farmer's N₂O emissions. The damage value is a function of the N rate and is calculated as $\phi(N) = 0.310 P_c e(N)$, where $e(N)$ is the quantity of N₂O emitted as a function of N, P_c is the market price of CO₂, and 0.310 is the GWP equivalence between tons of CO₂ and

kilograms of N₂O. More precisely, a regulatory agency sets up an incentive program to induce farmers to reduce N fertilizer applications by distributing offsets (credits) for the carbon equivalent value of their direct N₂O emission reductions.

The incentive payment structure will need to account for the increasing and nonlinear relationship between N₂O emissions and N applications. In panel (a) of figure 2, the fertilizer rate (in kg N/ha) is plotted against expected emissions (in kg N₂O/ha/year). Based on this curve, we calculate the curve representing the market value of total damage, denoted by $\phi(N)$, as explained above².

With an offset program in which farmers are paid by their emissions (or application) reductions, the optimization problem becomes

$$\max_{[N]} EU(\tilde{\pi}) = \max_{[N]} EU(\tilde{P}\tilde{y}(N) - P_N N + \phi(\bar{N}) - \phi(N))$$

where $[\phi(\bar{N}) - \phi(N)]$ is the dollar payment received by the farmer for reducing nitrogen applications from \bar{N} to N . Note that reductions are measured relative to \bar{N} , usually called the business-as-usual (BAU) or baseline rate, which is what the farmer would have applied in the absence of the incentive program. With the mentioned per hectare payoff structure, the participating farmer receives a payment equal to zero when application equals \bar{N} (because these applications imply zero N₂O emission reductions), and the payment increases nonlinearly as the farmer reduces the applications. With our assumptions of linear utility and uncorrelated yield and output prices, the FOC is $\bar{P} \frac{\partial \tilde{y}(N)}{\partial N} = P_N + \phi'(N)$. The farmer's maximization is achieved when expected marginal value product equals marginal cost plus the value of emissions from a marginal unit of fertilizer applied, $\phi'(N)$. The term $\phi'(N)$ increases the marginal cost of applying nitrogen (i.e., shifts the marginal damage curve up as shown in panel (b) of figure 2)

because it represents the marginal dollar amount that the farmer forgoes for each kilogram of N that is applied. The solution, denoted as N^* , is shown as point B, and the associated quantity of N_2O emissions is shown in panel (a). Therefore, given the decreasing marginal value product, the new optimality implies a reduction in N rates and N_2O emissions.

The marginal damage curve $\phi'(N)$ faced by a farmer under the program can shift for two reasons: (i) a change in the price of carbon, and (ii) a change in the emissions rate generated by a given N application. In the first case, a higher price of carbon implies a higher opportunity cost of applying fertilizer, because the fertilizer application reductions are more valuable, so we should expect greater reductions in fertilizer applications (and emissions). In the second case, different farm management practices (tillage; fertilizer type, depth, and timing; manure application) induce different emissions for the same quantity of N fertilizer applied. So if the farmer changes to a management practice that emits more, the value of $\phi'(N)$ will be higher, the opportunity cost of fertilizer applications will increase, and we should expect the farmer to apply less fertilizer. However, in this case, the expected marginal product might also change because the production function is affected by the use of a different management practice, and therefore we cannot unambiguously say the direction of the fertilizer applications change.

This offset payment program will induce the same N application reductions as a tax imposed on the purchases of the N input, provided the following conditions are met. (i) The tax structure, which according to panel (a) of figure 2 implies an increasing (progressive) tax rate, has a revenue curve (as a function of the N rate) that is equal to the total value damage curve $\phi(N)$. (ii) The tax rate has to adjust to the annual changes in the

market price of carbon. In this case, the farmer's problem is $\max_{[N]} EU(\tilde{\pi}) = \max_{[N]} EU(\tilde{P}\tilde{y}(N) - P_N N - \phi(N))$. With the linear utility and uncorrelated yield and output prices assumptions, the FOCs are $\bar{P} \frac{\partial \tilde{y}(N)}{\partial N} = P_N + \phi'(N)$, which are the same as in the offset program. Therefore, the solution (the optimal N^*) and the nitrogen application reduction are the same. Clearly, however, the distributive or welfare effects of each policy are different.

Outline of the Model

The offset program takes into account two important factors. First, the input decision is made under uncertainty coming from both the stochastic production function and output prices. Second, the market value of N₂O emissions as a function of N fertilizer application rates $\phi(N)$ and its first derivative $\phi'(N)$ are nondecreasing and nonlinear. Emission reductions are measured relative to a BAU, which are those emissions consistent with the optimal rate (\bar{N}) had the farmer not participated in the program.

At the beginning of the planting season, the farmer decides whether or not to participate in this incentive program. If he does not participate, the fertilizer rate will be consistent with a standard maximization problem. But if he chooses to participate, profits will be affected by an incentive payoff proportional to the N input reduction.

Consider first the case of a nonparticipating farmer who maximizes expected utility of per hectare profits³ by choosing the optimal nitrogen application rate, N^* . He solves the following problem: $\max EU(\tilde{\pi}_0) = \max_{[N]} \int_0^\infty \int_a^b U(\tilde{\pi}_0) h(P) f(y|N) dy dP$, where $\tilde{\pi}_0 = \tilde{P}\tilde{y} - P_N N$ is the farmer's random profit, randomness coming from uncertain output prices \tilde{P} and uncertain yields \tilde{y} . Yields behave according to a conditional density function $f(y|N)$ whose support is the non-negative closed interval $[a, b]$, a and b representing the

minimum and maximum yield possible, respectively. Output prices are governed by a probability density function $h(P)$ where $P \in [0, \infty]$. For ease of exposition, we first assume the distributions are independent, but later, in the simulations, we analyze the case of correlated yields and prices. Expectations (E) are taken with respect to both random variables, and $U(\cdot)$ is a concave twice continuously differentiable utility function. The FOC are $\int_0^\infty \int_a^b \left[U'(\pi_0)(-P_N)h(P)f(y|N) + U(\pi_0)h(P) \frac{\partial f(y|N)}{\partial N} \right] dydP = 0$. The solution is denoted by \bar{N} (the BAU), and we assume that the second derivative evaluated at \bar{N} is negative.

The participating farmer also maximizes expected utility of profits. The problem is as follows: $\max EU(\tilde{\pi}) = \max_{[N]} \int_0^\infty \int_a^b U(\tilde{\pi}_1)h(P)f(y|N)dydP$ where $\tilde{\pi}_1 = \tilde{P}\tilde{y} - P_N N + [\phi(\bar{N}) - \phi(N)]$. Uncertainty comes only from growing conditions and output prices that are reflected by the probability density functions $f(y|N)$ and $h(P)$, respectively. Therefore, he maximizes a standard expected utility problem but incorporating the mentioned payoff structure. The FOC are $\int_0^\infty \int_a^b \left[U'(\pi_1)(-P_N - \phi'(N))h(P)f(y|N) + U(\pi_1)h(P) \frac{\partial f(y|N)}{\partial N} \right] dydP = 0$ whose solution is denoted by $N^*(\theta)$, with $\theta = \{\bar{N}, P_N, \theta_0\}$, and θ_0 is the set of parameters of the function $\phi(\cdot)$ and the distributions $f(\cdot)$ and $h(\cdot)$. We assume the second derivative evaluated at N^* is negative. With $N^*(\theta)$, we are able to analyze the consequences of introducing this nonlinear offset program on the tradeoff between N rates and yields, and on the farmer's profitability.

From an implementation perspective, the regulatory agency has to know certain field characteristics (such as soil texture and slope) and management practices (crop rotation, tillage, quantity and type of fertilizer) to determine the payment function, baseline, and

optimal N application rates. Some can be observed by visual inspection but others, such as type and quantity of fertilizer applied, cannot. Moreover, farmers may have the incentive to misreport these values in order to claim more offsets than those consistent with the true N reductions. This poses an implementation problem that is not new to NPS pollution studies in agriculture. For example, the literature on water quality as affected by nitrogen, phosphorous, and pesticide pollution has acknowledged the issue of finding a cost-effective mechanism to monitor, verify, and enforce programs aimed to reduce on-farm nutrient use (Metcalf et al. 2007; Huang et al. 2001; Chowdhury and Lacewell 1996; Huang and LeBlanc 1994; Thomas and Boisvert 1994; and Huang and Lantin 1993). Some recent initiatives (Millar et al. 2010; MSU-EPRI 2010; Government of Alberta 2010; DEFRA 2008) have proposed verification of N application rates using a combination of (preseason and late season) soil nitrate tests, late-season stalk nitrate tests, chlorophyll meter readings, remote sensing of soil and crop canopy properties, soil electrical conductivity maps, and on-site crop test strips with different fertilizer rates. A complement to these are the so-called Best Management Practices (BMP) in the use of fertilizers, such as the “Right Source-Rate-Time-Place (4R) Nutrient Stewardship” proposed by the International Plant Nutrition Institute (IPNI 2011) and the Nutrient BMP Endorsement for Crop Revenue Coverage Insurance (USDA-RMA 2003), which would reduce uncertainty about on-farm practices. For example, a program has been introduced in Alberta, Canada, to reduce N₂O emissions from the application of N fertilizer and uses, depending on the target reductions, ammonium-based fertilizers, slow/controlled release fertilizers, or inhibitors (right source); injected or band applications (right place); split applications in spring, and fall applications only if slow/controlled released fertilizers or

inhibitors are used (right time); and applications based on field variability requirements and nitrogen balance (right rate) quantified by digitalized soil maps, landscape position, grid soil sampling, satellite imagery, in-season stalk nitrate tests, and overviewed by a program accredited professional advisor (Government of Alberta 2010).

The Simulation Exercise

We assume that a representative farmer owns one hectare of land, chooses to plant on a continuous corn rotation, and decides to participate in the offset program to reduce N₂O emissions. The farmer solves the expected utility model described above. There exists an environmental regulatory agency that oversees the offset program and distributes carbon credits for N₂O emission reductions, reductions measured relative to the farm-specific BAU nitrogen rate, \bar{N} .

N₂O Emissions and the N Application Rate

Measures of N₂O emissions as a function of N application rates were collected from corn field experiments conducted in the northern U.S. and Canada. They consist of more than 20 studies summarized by Rochette et al. (2008); Grant et al. (2006); Li, Narayanan, and Harriss (1996); Bouwman (1996); and Thornton and Valente (1996). A list is available from the authors upon request. We fit the following emissions curve to the data:

$$e(N) = \begin{cases} \sum_{i=0}^{i=3} a_i (N_m)^i & N \leq N_m \\ \sum_{i=0}^{i=3} a_i N^i & N > N_m \end{cases}$$

where a_i are parameter estimates (shown in table 1) from a regression model applied to the mentioned data, and N_m is the nitrogen rate at which the estimated curve has slope equal to zero.⁴ This is consistent with the nonlinear relationship between emissions and the N rate shown in figure 1.

Assuming there exists a market price for CO₂ (P_c), that is, GHG emissions are negatively valued by society, this emissions curve is used by the regulatory agency to construct the offset payment structure that rewards N reductions by the market value of their environmental damage. This value is $\phi(N) = 0.310 P_c e(N)$, expressed in dollars per hectare. Therefore, the payment structure as a function of the optimal N (shown in figure 3), which pays reductions relative to the BAU rate, is $[\phi(\bar{N}) - \phi(N_m)]$ for $N \leq N_m$ and $[\phi(\bar{N}) - \phi(N)]$ for $N > N_m$. It implies that given \bar{N} , per hectare payments increase from zero up to their maximum $[\phi(\bar{N}) - \phi(N_m)]$, as the farmer reduces the optimal N rate.⁵ This nonlinear payment structure should give more efficient results because if the objective is to reward emissions reductions, a “flat” payoff to all application rates as suggested by IPCC-Tier 1⁶ or a per unit nitrogen tax will not capture the implicit emissions behavior and thus will not provide correct signals to farmers.

Table 1. Estimation Results of Emissions Curve: $e(N)$

	α_0	α_1	α_2	α_3
Coefficient	1.09801	0.03640	-3.9874E-04	1.2758E-06
Standard error	0.33864	0.01713	1.8446E-04	5.1955E-07
t-stat	3.24243	2.12474	-2.16164	2.45554

It has to be noted that for a given N rate, different weather conditions will generate different levels of emissions. However, when determining the marginal payment structure, the regulator uses emissions at average weather conditions allowing the farmer to optimize under a known payment rate.⁷ This assumption is relaxed in the last section.

Estimation of a Conditional Yield Distribution

The yield response to nitrogen was estimated using 1987 to 1991 data from field-plot experiments on continuous corn conducted on four different farms spread throughout

Iowa. Yields were updated to 2010 levels using a proportional yield adjustment based on Iowa corn yield growth.

One of the objectives of the experiments was to isolate the effect on yields of increasing nitrogen application rates, leaving everything else constant. This dataset was also used in past studies by Babcock and Hennessy (1996) and Roosen and Hennessy (2003). The experiment consisted of 10 nitrogen application rates (0, 25.06, 56.10, 84.14, 112.18, 140.23, 168.28, 224.37, 280.46, 336.55 kg N/ha)⁸ with three replications on each of the four farms (sites) and in each of the five years. So there are 600 observations or 60 observations for each N application rate. Table 2 shows mean and standard deviation of corn yields by site and by year.

Following Babcock and Hennessy (1996), we assume that, conditional on a given N application rate, yields behave according to a beta distribution with shape parameters p and q . We further assume that yield randomness comes from the interaction of factors that are unobserved by the researchers (such as weather, pests, and management practices). The beta distribution is usually specified because it describes the nonsymmetric historical behavior of yields with respect to these unobservables.

Table 2. Yields (tons per hectare) from Continuous Corn Field Experiments in Iowa

	Yields by site				Yields by year				
	1	2	3	4	1987	1988	1989	1990	1991
Mean	11.57	11.71	12.46	11.11	13.28	7.41	12.69	12.89	12.30
	(3.28)	(4.21)	(4.28)	(3.12)	(3.00)	(2.60)	(3.66)	(3.31)	(2.84)

Note: Standard deviation in parentheses.

The moments of the yield distribution depend on the N application rate, and given that moments of the beta distribution are completely defined by the shape parameters, we specify them as a function of N rate, that is, $p(N)$ and $q(N)$. Then the conditional beta distribution can be written as

$$f(y|N) = \frac{\Gamma[p(N) + q(N)]}{\Gamma[p(N)]\Gamma[q(N)]} \frac{(y - y_{min})^{p(N)-1} (y_{max} - y)^{q(N)-1}}{(y_{max} - y_{min})^{p(N)+q(N)-1}} \quad (1)$$

where Γ is the Gamma function, $p(N) = p_0 + p_1N^{0.5} + p_2N$ and $q(N) = q_0 + q_1N^{0.5} + q_2N$. Parameters $p_0, p_1, p_2, q_0, q_1, q_2$ are estimated by maximum likelihood (shown in table 3). By feeding (1) with one value of N rate, we obtain the distribution of yields conditional on that N.

Table 3. Maximum Likelihood Estimation of Beta Parameters

Functional forms: $p(N) = p_0 + p_1N^{0.5} + p_2N$; $q(N) = q_0 + q_1N^{0.5} + q_2N$					
\hat{p}_0	\hat{p}_1	\hat{p}_2	\hat{q}_0	\hat{q}_1	\hat{q}_2
4.160	-0.114	0.005	12.832	-1.377	0.043
(0.515)	(0.094)	(0.005)	(1.416)	(0.205)	(0.008)

In figure 4 we see how the first two moments of the estimated yield density change with the N rate. From equation (1) we draw beta deviates for any given nitrogen application rate using the inversion method.

Simulation of Correlated Yields and Price Draws

The optimization problem is to maximize expected utility of profits, where uncertainty comes from both random yields and random output prices. Random corn prices were generated assuming a lognormal distribution. This is a standard assumption given that the percentage change of commodity prices can be approximated by a normal distribution with certain mean and variance, and therefore the variable in levels (the commodity price) is lognormally distributed (Hull 2009, p. 271). So the price vector $P \sim \log N(\mu, \sigma^2)$ is generated from the equation $P_r = e^{\mu + \sqrt{\sigma^2} Z_{1r}}$, where $\mu = \log(E(P)) - \frac{\sigma^2}{2}$, and $\sigma^2 = \log(volat^2 + 1)$.⁹ P_r is the r^{th} commodity price deviate generated; Z_{1r} indicates the r^{th} deviate from the random variables Z_1 distributed standard normal; $E(P)$ is the mean of

corn prices; and $volat = \frac{\sqrt{V(P)}}{E(P)}$ is the volatility of corn prices interpreted as the percentage change of prices with respect to their mean. The mean of corn prices $E(P)$ was set equal to \$151.69 per ton, which is the average of the Chicago Mercantile Exchange (CME) quotation on April 1 and April 15 of the December futures price for 2010. Price volatility was calibrated at 0.29 and calculated using the implied volatility from Blacks with an “at the money” call option on corn futures on the same days.

We remove the independence assumption between corn prices and yields of the previous section by following Johnson and Tenenbein (1981) to generate correlated draws from these two distributions. Given a target level of correlation ρ , the method consists of generating draws from two standard normal random variables Z_2 and Z_3 and creating another random variable Z_1 as a linear combination of the previous two. The linear combination is what creates correlation between Z_1 and the other variables. The linear combination weight is optimally selected so that the target correlation is achieved. By plugging Z_1 into the random price generator formula and by substituting Z_2 by a vector of randomly generated corn yields, we obtain correlated corn and yield draws.¹⁰

Maximization of Expected Utility of Profits

First, we solve the problem of a non-participating farmer (and denote the solution as \bar{N}). To this end, we generate $R=1000$ random draws of correlated yields and corn prices and use a line-search algorithm to find a value of N that maximizes the expression $EU(\tilde{\pi}) = \frac{1}{R} \sum_{r=1}^R U(P_r y_r - P_N N)$, where y_r and P_r are the r^{th} draw of yield and corn prices, respectively; P_N is a known price of nitrogen; and $U(\cdot)$ is assumed to be a constant absolute risk aversion (CARA) utility function of the form $U(\tilde{\pi}) = -e^{-ra\tilde{\pi}}$, where

$ra = -\frac{u''}{u'}$ is the coefficient of absolute risk aversion. The risk aversion coefficient was set as a value consistent with a risk premium equal to 0%, 25%, and 50% of the standard deviation of profits.¹¹ Other studies (Babcock, Choi, and Feinerman 1993; Babcock and Hennessy 1996; Hennessy, Babcock, and Hayes 1997) have set the risk aversion coefficient such that the risk premium is equal to a certain percentage of revenue. As this percentage increases, the individual is willing to pay more money to avoid the risk, implying a more risk-averse agent.

We then solve the problem of a participating farmer who takes as given the values of \bar{N} , P_N , and the payoff structure $\phi(\cdot)$, and maximizes the expected utility of profits conditional on R correlated draws of yields and corn prices. Then, the expression to be maximized by the farmer is

$$EU(\tilde{\pi}) = \begin{cases} \frac{1}{R} \sum_{r=1}^R U[P_r y_r - P_N N + \phi(\bar{N}) - \phi(N_m)] & \text{if } N \leq N_m \\ \frac{1}{R} \sum_{r=1}^R U[P_r y_r - P_N N + \phi(\bar{N}) - \phi(N)] & \text{if } N > N_m \end{cases}$$

We again use a line-search algorithm to find the maximum, and denote the solution as N^* . With \bar{N} and N^* , we can find the nitrogen application reduction, and also the payment the farmer receives from the program.

Simulation Results for Nitrogen Application Rate

We present in table 4 results of the expected utility optimal application rate induced by participating in the offset program (N^*), the BAU nitrogen application rate (\bar{N}), the reduction of N applied, the yield loss for applying less N , the incentive payment received by the farmer, and the change in the farmer's profits due to participation. We use carbon prices of \$15, \$30, and \$45 per ton, and various risk-aversion coefficients and price-yield correlations.¹²

Table 4. Results of the N₂O Emissions Reductions Incentive Program (per hectare)

Carbon Price, $P_c = \\$15/\text{ton CO}_2$						
RP (%)	N^* (kg)	\bar{N}(kg)	N reduct.	Yield loss (%)	\$ payoff	π increase
~0	229	237	8.67	0.35	2.36	1.27
25	226	236	9.20	0.40	2.41	1.31
50	223	233	9.80	0.46	2.45	1.34
Carbon Price, $P_c = \\$30/\text{ton CO}_2$						
RP (%)	N^* (kg)	\bar{N} (kg)	N reduct.	Yield loss (%)	\$ payoff	π increase
~0	222	237	15.19	0.69	7.83	4.46
25	220	236	16.00	0.77	7.91	4.54
50	216	233	16.89	0.88	7.95	4.60
Carbon Price, $P_c = \\$45/\text{ton CO}_2$						
RP (%)	N^* (kg)	\bar{N} (kg)	N reduct.	Yield loss (%)	\$ payoff	π increase
~0	217	237	20.40	1.00	15.08	8.95
25	214	236	21.37	1.11	15.12	9.07
50	211	233	22.42	1.25	15.05	9.13

Notes: Risk premium (RP) is the % of the standard deviation of profits. The corn price is \$151.70/ton, and the N price is \$726.87/ton. Yield and corn price correlation $\rho = -0.30$.

With a carbon price of \$30/ton, a participating farmer whose absolute risk-aversion coefficient is consistent with a risk premium equal to 25% of the standard deviation of profits optimally reduces his nitrogen applications by 16.00 kg/ha for participating in the program and obtains an incentive payment of \$7.91 per hectare. The increase in profits is \$4.54 per hectare because lower variable costs are offset by a yield penalty.¹³ So the offset program induces N rate reductions of 7% but a yield penalty of less than 1%.

Results are driven by the estimated parameters of the emissions curve $e(N)$. A 90% confidence interval for this curve illustrates how results would change. With P_c at \$30 and the risk premium at 25%, the lower extreme of the interval indicates that farmers reduce optimal N applications by 11 kg/ha and receive a payment of \$3.75, while at the upper extreme, N reductions are 19 kg/ha and offset payments are \$12.18.

In comparative statics results that, for reasons of space are not presented here, we show that, first, the more risk-averse farmer optimally applies a lower nitrogen rate than

the less risk-averse farmer. It can be shown that, at this level, N is a risk-increasing input. Second, the more risk-averse farmer optimally makes a higher reduction in applications when participating in the offset program. This comes from the fact that, abstracting from the incentive payment, profits of the more risk-averse farmer are lower because of the yield penalty; therefore, when faced with a certain offset payment, he will reduce the N applications by a greater amount because this certain payment represents a higher proportion of the uncertain profits.¹⁴

Estimation of a Distribution of Emission Reductions

We need to know, before the planting season starts, the distribution of emission reductions that will be induced by the program. Actual end-of-season N₂O emission reductions depend on random weather (rainfall and temperature in our particular case). To this end, we simulate the weather effects on the N₂O emissions induced by the optimal N application reduction ($\bar{N} - N^*$) of the participant farmer.¹⁵

Distribution of Rainfall and Temperature

To simulate random weather, we fit nonparametric density functions to Iowa rainfall and temperature time series (1895-2008) from the National Climate Center at the National Oceanic and Atmospheric Administration using an Epanechnikov kernel (DiNardo and Tobias 2001).¹⁶ Rainfall is the total annual precipitation for the state and is measured in centimeters per year (cm/yr).¹⁷ Temperature is the annual average temperature for the state measured in degrees Celsius. Rainfall density was bell-shaped with an average of 89 cm/yr (range 56 to 122), and temperature density averaged 8.8 degrees (7 to 11). Random draws were generated from both densities. Because the correlation between the two series is virtually zero, we draw independently from both distributions.

Weather Effects on N₂O Emissions

Based on our data collection on applications of N fertilizer and N₂O emissions, we estimate a response curve using the following regression model: $\epsilon(N) = \sum_{i=0}^{i=3} a_i N^i$.¹⁸ Given that data from these studies covered different years, we assume that the fitted curve represents the behavior of emissions for average weather conditions. From this curve we calculate the levels of emissions at N^* and \bar{N} . The effects of precipitation and temperature on N₂O emissions are obtained by running the Denitrification-Decomposition (DNDC) model calibrated for a continuous corn rotation in Iowa (Li, Narayanan, and Harriss 1996) with different N application rates. Table 5 and the upper panels of figure 6 (blue circles) show the response of N₂O emissions to changes in precipitation (temperature), holding temperature (precipitation) fixed at its average, $N^* = 220$ kg N/ha, and holding all other variables at baseline levels.¹⁹

Table 5. Sensitivity of N₂O Emissions to Changes in Precipitation and Temperature

Annual Precipitation		Annual Average Temperature	
Precipitation cm/year	N ₂ O-N kg/ha/yr	Temperature °C/year	N ₂ O-N kg/ha/yr
56.0	7.62	-	-
68.7	6.73	7.0	2.81
78.7	5.61	7.8	2.93
86.0	3.98	8.7	3.38
98.7	4.38	9.8	3.33
108.7	3.93	10.8	3.94
118.7	3.48	11.8	3.99

The levels of emissions for each draw of the weather variables are obtained by a cubic spline interpolation²⁰ of the results of the DNDC runs. The continuous lines in the upper panels of figure 6 show both interpolated curves at N^* and \bar{N} . With these functions we obtain the level of emission reduction induced by the optimal N application reduction ($\bar{N} - N^*$) for each draw of the weather variables.

Simulation Results for the Expected Reduction in Emissions

The results are presented as histograms in figure 7, for both precipitation and rainfall, in kilograms of carbon dioxide equivalent (kg CO₂e). Panel (a) shows the distribution of the per hectare emission reductions for random precipitation holding temperature at the average. Average emission reductions are 323 kg of CO₂e, ranging between 227 and 490. The particular shape of this distribution is associated with the behavior of emissions as precipitation changes, as is shown in the upper panel of figure 6. The dollar value of the average emission reduction is \$9.70 per hectare, which is comparable to the \$7.91 received by the farmer. This suggests that the nonlinear offset program provides the correct price signals to farmers.²¹

The distribution of N₂O emission reductions as affected by random temperature shown in panel (b) of figure 7 also has a shape determined by how emissions are affected by temperature. It has an average value of 257 kg of CO₂e per hectare per year, ranging between 232 and 322. Its dollar value is \$7.70.

These high levels of N₂O emission reductions are driven by the nonlinear payoff scheme. If we were to consider a linear payoff structure such as that proposed by the IPCC Tier-1 (where the N₂O response to N is approximated by a linear curve with a slope of 0.0125), a participating farmer would reduce N applications by 5 kg N/ha (from 236 to 231), receiving a payment of less than \$1. Or in order to make a comparable emission reduction of 323 kg of CO₂e (that in the nonlinear scheme is achieved by an N application reduction of 16 kg/ha, and a yield penalty of 0.77%), under this linear scheme, farmers would have to inadvertently reduce applications by 84 kg/ha, inducing a yield penalty of 888 kg/ha (or 7%).

To show how much these emission reductions represent, consider first that an approximation of the continuous corn area in Iowa in 2010 was about 1.6 million hectares. Then, using the range obtained for random rainfall and assuming that all Iowa continuous corn farmers participate in the offset program, we get a reduction between 349 and 754 thousand tons of CO₂e, with an average of 497. The EPA Inventory of GHG for 2009 (U.S. EPA 2011) calculates N₂O emissions from the application of synthetic fertilizers on U.S. cropland and grassland at 40.8 million tons of CO₂e. Therefore, Iowa reductions based only on 2010 continuous corn would have been 1.2% of the total emissions from the application of synthetic fertilizer on U.S. cropland and grassland.

Conclusions

The overapplication of nitrogen by corn growers, while optimal from an ex ante perspective, has negative environmental consequences. In this article, we present a nonlinear offset program designed to induce farmers to reduce their nitrogen applications and, as a result, reduce N₂O emissions from agriculture. The offset program targets the nitrogen applications because of the NPS nature of the emissions. A representative farmer maximizes expected utility of per hectare profits by choosing the optimal nitrogen application rate. Reductions are measured relative to the BAU nitrogen rate. The nonlinearity of the payoff structure is consistent with the nonlinear relationship between N₂O emissions and nitrogen application rates. This instrument is far more efficient than traditional linear schemes because it transmits price signals that are aligned with the true N₂O behavior and the ultimate objective of the program.

The key insight in the article is driven by the simulation results. These show that with a very modest carbon price of \$30, a farmer with a low risk aversion level reduces

his nitrogen applications by about 7% as a result of an offset payment of \$7.91 per hectare. A more risk-averse farmer applies less nitrogen because, for these particular application rates, nitrogen fertilizer is a risk-increasing input. We also found that the more risk-averse farmer makes a higher application reduction, of about 7.3%, and receives an offset payment of \$7.98 per hectare. In both cases the expected yield reduction is minimal (about 1%) because the program targets nitrogen applications that in most years are surplus relative to crop needs.

We also present the distribution of emission reductions induced by the presence of the offset program that takes into account a priori unknown weather variables. We find that, for random rainfall and fixed temperature, the distribution of emission reductions averages 323 kg CO₂e per hectare, with a shape depending on how emissions respond to rainfall. For random temperature and fixed rainfall, the average reduction is 257 kg CO₂e per hectare. These emission reductions are achieved with a yield penalty of less than 1%, whereas a linear scheme with the same target of emission reductions will result in a yield penalty of 7%.

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Figures

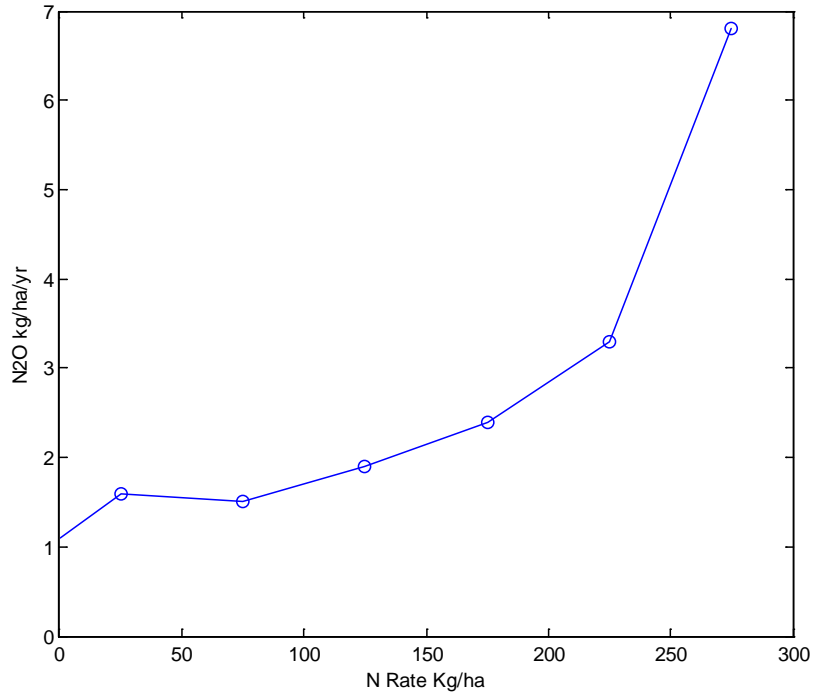


Figure 1. Average N₂O emissions as a function of N rates

Source: Based on table 5, Bouwman, Boumans, and Batjes (2002)

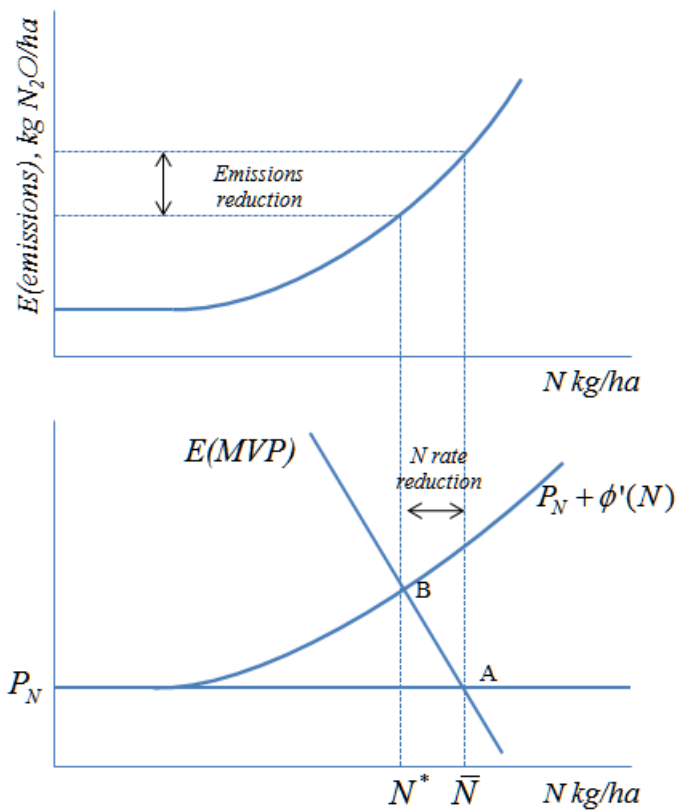


Figure 2. Panel (a) N_2O emissions as a nonlinear function of nitrogen rates, and N_2O emission reductions from the incentive program

Panel (b) Optimal nitrogen application rate of a nonparticipating farmer (point A) and a participating farmer (point B) and optimal nitrogen application reductions

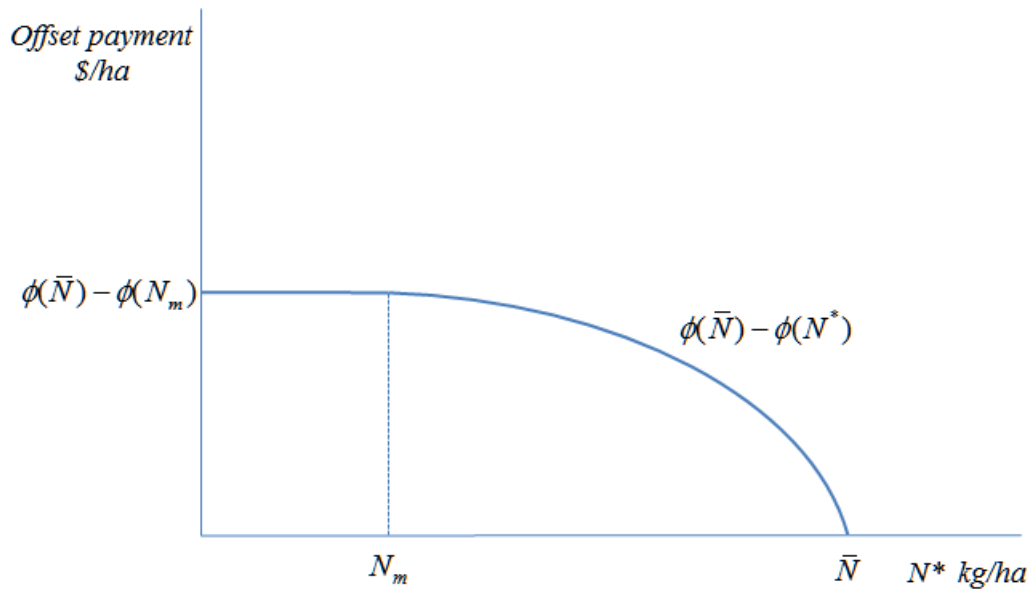


Figure 3. Offset payment structure as a function of the optimal nitrogen application rate N^*

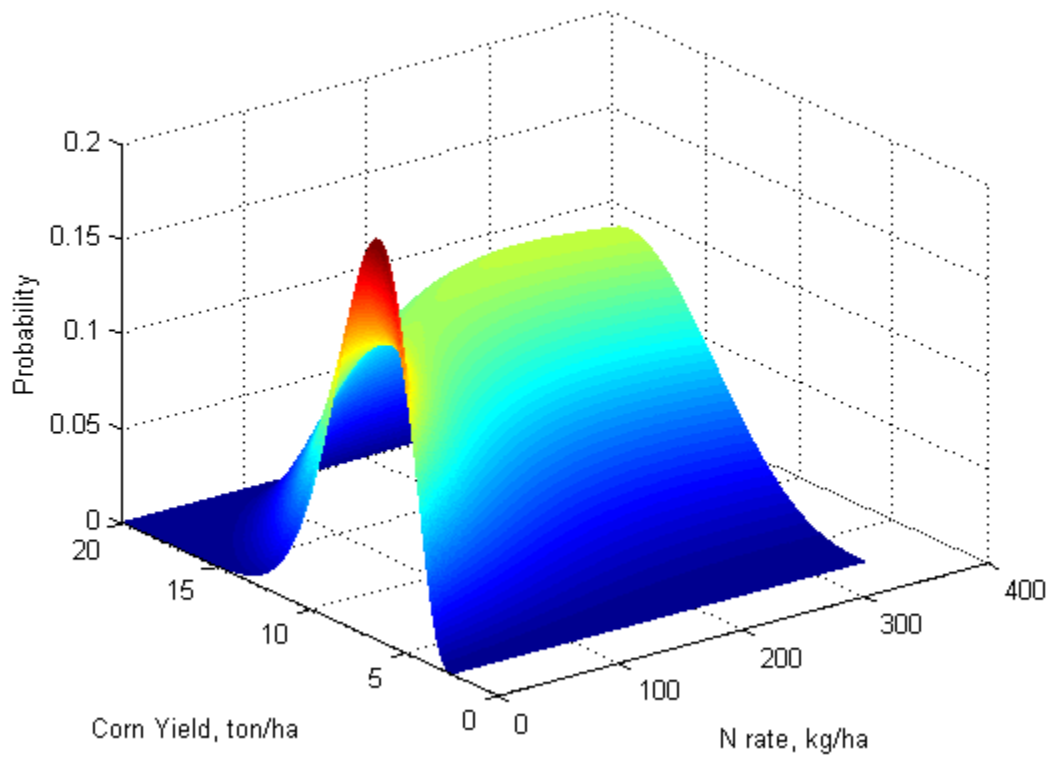


Figure 4. Parametric estimation of a conditional beta probability density function of Iowa corn yields for different N rates

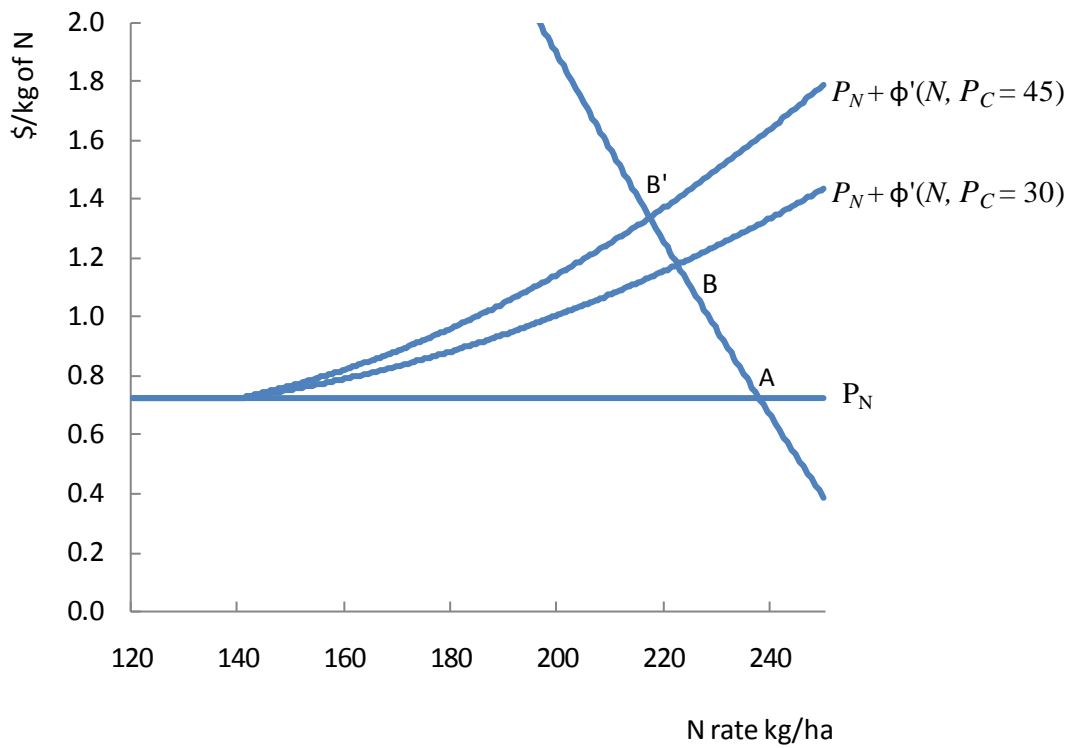


Figure 5. Expected marginal value product (EMVP) curve, and marginal cost curves when carbon price P_c is zero, \$30, and \$45

Note: The intersections show the optimal solution of the linear utility maximization problem for the different P_c scenarios: A = (237, 0.727), B = (222, 1.051) and B' = (217, 1.159).

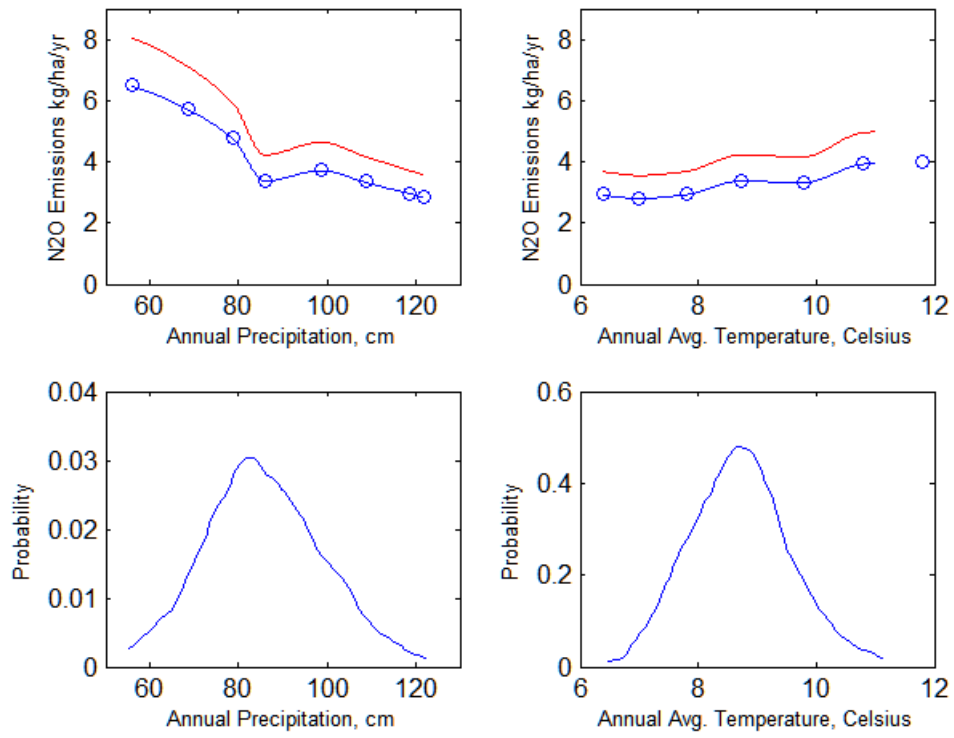


Figure 6. Random weather and response of N₂O emissions

Note: Upper panels show the variation of emissions as a function of average precipitation and average temperature at $N^* = 220$ kg N/ha (blue) and $\bar{N} = 236$ kg N/ha (red). Circles show available data and the blue line the interpolated values. Lower panels represent nonparametric probability density function of precipitation and temperature using an Epanechnikov kernel.

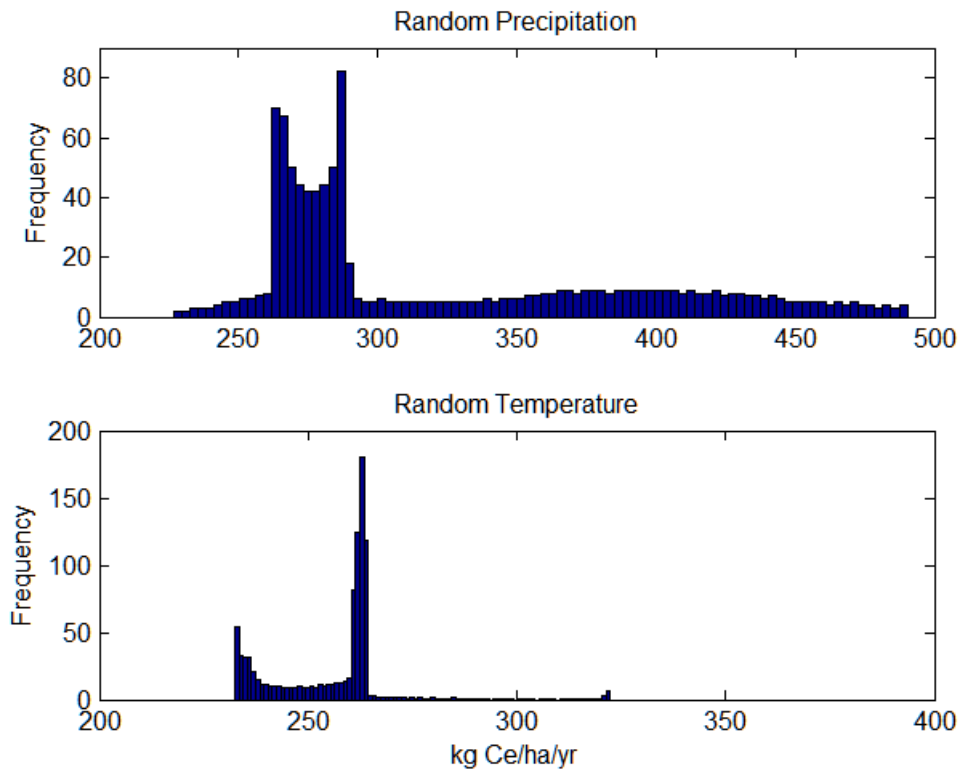


Figure 7. Histograms of N₂O emission reductions (kg of carbon equivalent per hectare) for random precipitation (panel a) and random temperature (panel b), induced by an optimal N application reduction of $(N^* - \bar{N}) = 16.00$ kg N/ha, when $P_c = \$30/\text{ton CO}_2$

Endnotes

¹ In the next section we remove the linearity and independence assumptions and solve the expected utility problem under risk aversion and correlated random deviates of yield and prices.

² Alternatively, a risk-averse social planner, which values (positively) farmers' utility and (negatively) the uncertain emissions curve, maximizes its utility by choosing the socially optimal parameters of the payoff structure. Then this optimal structure is faced by farmers in their expected utility maximization problem.

³ In the previous section, for exposition, we assumed a farmer who maximizes under a linear utility. In what follows, we assume a utility that can accommodate different degrees risk aversion. We compare results using different risk aversion levels and conclude that the results are very similar.

⁴ For the estimated curve N_m equals 141 kg/ha.

⁵ Payment no longer increases for reductions beyond N_m because the incentive program has a superior objective of not harming crop yields excessively. If carbon prices turn high enough, it could be optimal for the farmer to apply an extremely low N fertilizer rate (high N reduction), affecting crop yields and possibly food and feed supply.

⁶ The Intergovernmental Panel on Climate Change (IPCC) assumes that N₂O emissions are a constant proportion of 1.25 +/- 1% of N applications (Bouwman 1996).

⁷ The rationale of this assumption is that if we average a farmer's emission reductions over several years, they will be consistent with the incentive payment received in each year.

⁸ These are, respectively, 0, 25, 50, 75, 100, 125, 150, 200, 250, and 300 pounds per acre.

⁹ Proof is available from the authors upon request.

¹⁰ We selected two levels of correlation, one negative and one positive. Negative correlation would exist because when corn prices increase, farmers have the incentive to plant more corn, substituting land away from other uses. If that new corn land is of lower productivity, we can expect a yield decrease. Positive correlation might occur if higher prices induce changes in management practices with the objective of obtaining higher yields (using high-yielding seeds or different types of fertilizers or herbicides).

¹¹ The risk premium (RP) is the dollar amount an individual is willing to pay to avoid a risky bet and receive a certain profit. For our utility function, the risk premium is found to be $RP = E(\tilde{\pi}) + \frac{1}{ra} \log [E(e^{-ra\tilde{\pi}})]$.

¹² Throughout the estimation we assumed a nitrogen price of \$726/ton, equivalent to \$0.33/lb suggested by Iowa State University Extension for continuous corn (Duffy 2009).

¹³ We also solved the model with linear utility which is equivalent to a risk premium equal to zero. Results, shown in table 4, are very similar: for carbon prices of \$30, optimal N application reductions are 15.19 kg N/ha (237-222) with a payment of \$7.83, so the degree of risk aversion does not affect the main conclusions. Figure 5 shows the estimation of what is discussed in figure 2: N application reductions of 15.19 kg N/ha (237-222) at carbon prices of \$30, and of 20.4 kg N/ha (237-217) at \$45.

¹⁴ We solved the model with a positive correlation ($\rho=30$), and results were very similar.

¹⁵ For this simulation we select the scenario of $P_c = 30$, $RP = 0.25$ and $\rho = -0.30$.

¹⁶ Bandwidth = $h = 0.9 \left(\min \left\{ \hat{\sigma}, \frac{IQR}{1.34} \right\} \right) n^{-\frac{1}{5}}$; $\hat{\sigma}$ is the sample standard deviation; IQR is the interquartile range (difference between the 75th and 25th percentile), and n is the number of observations.

¹⁷ One inch of rain equals 2.5 cm.

¹⁸ Not restricting the response curve for values of N less than N_m does not affect the results because the portion of interest of the curve is to the right of N_m .

¹⁹ Baseline scenario values are N concentration in rainfall, 1.6 mg N/liter; soil texture loam, clay 19%; pH, 6.0; bulk density, 1.4 g/c.c.; soil organic carbon, 0.025 kg C/kg; fertilizers, 37.5 kg nitrate-N, 37.5 kg ammonium-N, 75.0 kg anhydrous ammonia-N/ha applied on April 25 at surface; soil tilled with disks on April 15 and with moldboard on October 15; neither manure nor irrigation applied.

²⁰ This method fits a piecewise cubic function between each of the given points (knots).

²¹ The difference arises because, at the optimum, the slope of the emissions curve used by the regulatory agency, 0.046, is slightly lower than that obtained with the interpolation, 0.065.