Quantifying Co-Benefits of Water Quality Policies: An Integrated Assessment Model of Land and Nitrogen Management

Authors:

Weizhe Weng[1], Kelly M. Cobourn[2], Armen R. Kemanian[3], Kevin J. Boyle[4], Yuning Shi[5], Joseph Stachelek[6], Charles White[3]

Affiliations:

[1]Food and Resource Economics Department, University of Florida, Gainesville, Florida, USA, 32611, USA

[2]Department of Forest Resources and Environmental Conservation, Virginia Tech, Blacksburg, Virginia, 24061, USA

[3]Department of Plant Science, The Pennsylvania State University, University Park, Pennsylvania, 16802, USA

[4]Department of Agricultural and Applied Economics, Virginia Tech, Blacksburg, Virginia, 24061, USA

[5]Department of Ecosystem Science and Management, The Pennsylvania State University, University Park, Pennsylvania, 16802, USA

[6]Division of Earth and Environmental Sciences, Los Alamos National Laboratory, Los Alamos, New Mexico, 87545, USA

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Abstract

Due to the nature of nitrogen cycling, policies designed to address water quality concerns have the potential to provide benefits beyond the targeted water quality improvements. For example, actions to protect water quality by reducing nitrate leaching from agriculture also reduce emissions of nitrous oxide, a potent greenhouse gas. These positive effects that are incidental to the regulation's intended target are termed "co-benefits." To quantify the co-benefits associated with reduced nitrate leaching, we integrate an economic model of farmer decision making with a model of terrestrial nitrogen cycling for the watershed surrounding Lake Mendota, Wisconsin, USA. Our model results highlight that the co-benefits from nitrous oxide abatement are substantial, and their inclusion increases the benefit-cost ratio of water quality policies. Our modeling approach provides a framework that links air and water pollutants in an agri-environmental system and offers a direction for future studies.

1. Introduction

Nitrogen applied in the form of commercial fertilizer is a key input for agricultural production. The use of fertilizers boosts crop yields, but the application of nutrients exceeding crop needs contributes to environmental degradation in a myriad of ways. For example, commercial fertilizer use degrades water quality and exacerbates climate change (Woodward 2011). Excess nitrogen in the form of nitrate (NO_3^-) leaches through the soil and into surface and groundwater, contributing to the eutrophication of surface water bodies, contaminating drinking water supplies, and adversely affecting human health (Smith et al. 1999). At the same time, excess nitrogen is emitted in the form of nitrous oxide (N_2O), a greenhouse gas with high global warming potential.

Due to the nature of nitrogen cycling and the joint production of nitrate and nitrous oxide, policies designed to protect water quality have the potential to provide benefits by also reducing greenhouse gas emissions. The nitrous oxide emission reductions, which are favorable to human welfare but incidental to the policy's intended water-quality target, are often referred to as "co-benefits" (Aldy et al. 2020). The literature on policies for climate change mitigation explicitly considers such co-benefits (Feng et al. 2007; Nemet et al. 2010; Ürge-Vorsatz et al. 2014), but we are aware of only one study (Gasper et al. 2012) that has evaluated co-benefits that arise in the context of policy for water quality.[1]

In this paper, we quantify the co-benefits from reductions in nitrous oxide emissions that arise when actions are taken to reduce nitrate leaching to protect water quality. To do so, we develop an integrated assessment model that tightly couples a constrained optimization model of

[1]Gasper et al. (2012) describes the climate co-benefits of Maryland's water quality trading program and the impacts on the implementation of best management practices (BMPs). Our study differs from Gasper et al. (2012) in terms of methodology and policy targets.

agricultural land and fertilizer-use decision making with an agronomic model of terrestrial nutrient cycling. Our model captures the feedback between farmer decision making and nutrient cycling— farmer decisions depend on nutrient cycling (via crop yields), and nutrient cycling depends on farmer decisions (via land and fertilizer use). We use the model to simulate the joint production of nitrate and nitrous oxide as a function of farmer decisions at the extensive margin, i.e., choice of crop rotation and land fallowing, and at the intensive margin, i.e., rate of fertilizer applications.

We apply our model empirically to the watershed surrounding Lake Mendota, Wisconsin, USA, which is dominated by agriculture and has a long history of water-quality degradation. Current and historic agricultural land-management decisions, such as the expansion of corn production and the excess use of commercial fertilizers, are the primary drivers of ongoing water quality concerns in the region (Cobourn et al. 2018, Lathrop, 2007). We impose a series of increasingly stringent nitrate leaching constraints within the model, ranging from a 5% to 95% reduction in leaching relative to the status quo.[2] Policies that limit nitrate leaching from agricultural production by imposing a cap on leaching are an important step in the restoration of basins with impaired water quality from excessive nutrient loading (Evans-White et al. 2013; Royer et al. 2006). For each leaching constraint, we calculate the associated change in nitrous oxide emissions and compare the benefit-cost ratio for a policy action to reduce only nitrate leaching (without considering co-benefits) versus a policy action to reduce both nitrate leaching and nitrous oxide emissions (considering co-benefits).

Our results suggest that, across nitrate leaching reduction scenarios, nitrous oxide emissions decline in proportion to changes in nitrate leaching: a 10% reduction in leaching is

[2] In practice, evaluation of nitrate leaching reductions could be achieved by edge-of-field monitoring (Daniels et al. 2018). Farmers could fulfill water quality targets by nutrient management or adoption of best management practices.

associated with a 12% reduction in emissions and a 30% reduction in leaching is associated with a 27% reduction in emissions. However, the co-benefits from reduced nitrous oxide emissions vary substantially across years due to interannual variation in relative crop prices and weather. Variation in relative crop prices affects the adjustments made by farmers to meet the leaching reduction constraint. Variation in weather, particularly in the timing and amount of precipitation, affects the production function for leaching and emissions. The importance to our results of interannual variability in weather conditions suggests that the co-benefits of actions to protect water quality are likely to shift over time as climate conditions evolve. Across years, we find that accounting for emissions co-benefits increases the benefit-cost ratio for each leaching reduction scenario.

This research makes three contributions to the literature: first, we highlight the importance of quantifying externalities of policy regulations, such as the co-benefits of greenhouse gas emissions of water policies. Correctly accounting for these co-benefits provides additional insight into the optimal design of, and benefits from, water quality regulations. Furthermore, the quantification of co-benefits could be critical to establishing efficient and effective environmental markets that incentivize environmental improvements (Liu and Swallow 2016). Second, our results provide an example of the "missing" benefits of water polices as indicated in Keiser et al. (2019). The direct production of water quality benefits is joint with the production of a myriad of other environmental benefits, including not only climate change mitigation, but also water quantity, terrestrial and aquatic habitat, biodiversity, and human health effects (Kroetz et al. 2020; Rabotyagov et al. 2014; Sample 1997; Olmstead 2010). Quantifying the missing categories of those benefits is important for the design of future water policies. Last, our modeling approach provides a framework that links air and water pollutants in an agri-environmental system and offers a direction for future studies. Our study site shares common feedbacks among ecosystem dynamics, human uses, social dynamics, policy and practice with other lakes (Carpenter et al. 2007). Our study provides a general framework that links these feedback mechanisms together, which can be readily extended to other watersheds in the Midwest and the rest of the country with watershed-specific parameters. Studies on other watersheds would benefit from the inclusion of climate co-benefits as a major step towards accounting for the total costs and benefits of water policy.

2. Data and Methods

To estimate the co-benefits from reduced nitrous oxide emissions due to actions that reduce nitrate leaching, we couple an economic simulation model of farmer decision making with a process-based, agronomic model of terrestrial nitrogen cycling. These models are connected via a two-way feedback loop in which farmer decisions depend on nutrient cycling (via crop yields), and nutrient cycling depends on farmer decisions (via land and fertilizer use). Fig. 1 describes our coupling approach, which includes two stages. In the first stage, we use the agronomic model to generate a suite of simulation results that provide input data to calibrate the economic decision-making model (Fig. 1a). We then use the calibrated economic model to simulate farmer adjustments in land and fertilizer use in response to progressively stringent constraints on nitrate leaching. Changes in land and fertilizer use provide the basis for estimating the joint production of nitrate leaching and nitrous oxide emissions (Fig. 1b).

We apply our coupled model empirically to the watershed surrounding Lake Mendota, Wisconsin, USA. This watershed is dominated by agriculture, which occupies 67% of the total land area (Fig. 2). Current and historic agricultural land-management decisions in this catchment are the primary drivers of ongoing water quality concerns in the region. For example, large nitrogen and phosphorus loads from the watershed have been shown to drive the development of phytoplankton blooms in the lake each summer (Cobourn et al. 2018; Farrell et al. 2020). Weng et al. (2020) demonstrate that these phytoplankton blooms that reduce water clarity are capitalized into (reduced) lakefront property values. Current studies and managements in Lake Mendota watershed have stressed phosphorus reduction programs, but much less attention has been given to nitrogen control mechanisms (Lathrop, 2007). This specific context demonstrates there is a clear need to develop modeling tools that are portable across watersheds to support informed decisions on nitrogen reduction policies to address water quality concerns.[3]

2.1 Economic Model of Agricultural Decision Making

To simulate farmer decision making, we develop a watershed-level constrained optimization model that is calibrated using positive mathematical programming (PMP).[4] Following the PMP literature (Garnache et al. 2017b; Heckelei and Wolff 2003; Maneta et al. 2020; Mérel et al. 2011, 2013), farmers choose their land allocation and fertilizer applications to maximize annual net returns subject to production technology and a land constraint. The PMP calibration ensures that the solution to the optimization problem, which represents aggregate decision making by all farmers within the watershed, reflects observed levels of input use and production over a reference period (Howitt 1995).

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[3] We focus on N since N contributes to both water quality degradation and greenhouse gas (GHG) emissions. Although P is a critical nutrient causing algal blooms in freshwater systems, P leaching does not contribute to GHGs, which is the co-benefit we are demonstrating. Different from N, the losses of P are both in soluble form and as sediment or associated to organic matter. The contribution of P to streams and lakes in watersheds is as much from current erosion as from remobilization of sediments that are already in the system. Modeling this fate transport is not part of the research that focuses on co-benefits.

[4] The aggregate modeling approach that we take, at the catchment scale, is consistent with the way in which remote sensing imagery is used within the Cycles model to determine the quantity of land in crop rotations.

We consider the decision to allocate land and fertilizer across a set of crop rotations and fallow lands. Three crop rotations are prevalent in our study area: continuous corn production, a two-year alternating corn-soybean rotation, and a six-year corn-alfalfa rotation consisting of three years of alfalfa followed by three years of corn. Modeling a choice among rotations is consistent with farmer decision making in practice (Livingston et al. 2015). Moreover, modeling the choice of rotation allows us to capture important differences in nitrogen uptake that arise from alternating corn with nitrogen-fixing soybeans and alfalfa, which affects fertilizer use decisions, nitrate leaching, and nitrous oxide emissions (Strock and Dalzell 2014). Although fallow land is not profitable, farmers would choose fallowing to fulfil water quality policies. [5]

Within our study region, nitrogen fertilizer is predominantly applied to increase corn yields, with the highest application rates for continuous corn. Growing corn in rotation with soybeans or alfalfa reduces the benefits of applying fertilizer to the corn crop. For example, there is little benefit to fertilizer applied to corn the first year following alfalfa because the corn plant has access to a reservoir of nitrogen fixed by the preceding year's alfalfa. The benefit from fertilizer applications increases in the second and third years of corn production following alfalfa, as subsequent years of corn draw down the available nitrogen stock. All else constant, the marginal benefits of applying nitrogen fertilizer increase in each year of continuous corn following a nitrogen-fixing crop.

From the standpoint of fertilizer needs and the environmental consequences of production, corn from one rotation or corn within different years in a rotation is effectively a unique crop, even if from the standpoint of commodity markets, the output (corn) is

[5] Similar with Goldstein et al. (2012) and Medellín-Azuara et al. (2012), we assume zero profits for fallow/idle land use. This may be a concern if farmers receive payments (i.e., through the CRP or EQIP programs) for idling lands. We avoid this problem by excluding lands that are never in crop production during our study period.

homogeneous. To capture this in our model, we define an index *m* that captures the combination of output commodity (corn (*c*), soybean (*s*), and alfalfa (*a*)), and rotation (cc, cs, ca, where *cc* denotes continuous corn, *cs* corn-soybean, and *ca* six-year corn-alfalfa). The index *m* defines the commodity within each rotation (crop) as *m = cc-c, cs-c, cs-s, ca-a1, ca-a2, ca-a3, ca-c1, ca-c2, ca-c3,* where *cc-c* denotes corn in a continuous corn rotation, *cs-c* denotes corn in corn-soybean rotation, *cs-s* denotes soybean in corn-soybean rotation, *ca-a1* denotes first year alfalfa in corn-alfalfa rotation, *ca-a2* denotes second year alfalfa in corn-alfalfa rotation, *ca-a3* denotes third year alfalfa in corn-alfalfa rotation, *ca-c1*denotes first year corn in corn-alfalfa rotation, *ca-c2* denotes second year corn in corn-alfalfa rotation, and *ca-c3* denotes third year corn in corn-alfalfa rotation. Each member of the set *m* has unique fertilization requirements due to differences in nitrogen fixation in the prior period(s). We let *t* index the growing season.

Following Mérel et al. (2011 and 2013), we define a general constant elasticity of substitution (CES) production function:

$$q_{mt} = \mu_m \left[\beta_{Lm} x_{Lmt}^{\rho_m} + \beta_{Nm} x_{Nmt}^{\rho_m}\right]^{\frac{\delta_m}{\rho_m}} \quad (1)$$

where q_{mt} denotes the production of crop *m* in year *t*, x_{Lmt} is area of land allocated by crop and year; and x_{Nmt} is the fertilizer application rate per unit land area by crop and year. The production function in eq. (1) depends on the parameters μ_m, β_{Lm}, β_{Nm}, δ_m, and ρ_m, which are to be determined in the calibration process (Fig. 1a). The parameter ρ_m is defined as $\rho_m = \frac{\sigma_m - 1}{\sigma_m}$, where σ_m is the elasticity of substitution between land and fertilizer inputs.

The aggregate farm decision in the watershed is represented as a constrained optimization problem in which the objective is to maximize the net returns to crop production, given by:

$$\max_{x_{Lmt}, x_{Nmt}} \sum_m \{p_{mt} q_{mt} - [(c_{Lm} + \lambda_{Lm}) x_{Lmt} + (c_{Nm} + \lambda_{Nm}) x_{Nmt}]\} \quad (2)$$

The first term in the summation of eq. (2) captures revenue earned from crop production, where p_{mt} is the market price for crop m in year *t* and crop output (q_{mt}) is defined by eq. (1). The remaining terms in eq. (2) capture the costs of land and fertilizer allocation decisions, where c_{Lm} is the per-unit cost of land allocated to crop *m;* c_{Nm} is the per-unit cost of nitrogen fertilizer for crop m; and the parameters λ_{Lm} and λ_{Nm} are unobserved cost adjustment parameters to be determined as part of the model calibration. The parameters λ_{Lm} and λ_{Nm} rationalize observed input costs and ensure the optimization model reproduces observed input use during the reference period. A positive value for either of these parameters indicates that there is an unobserved cost associated with the input's use in each rotation, whereas a negative value suggests an unobserved benefit.[6] In eq. (2), productive inputs other than fertilizer are assumed to be used in fixed proportion to land.[7,8] Similarly, the fertilizer inputs phosphorus (P) and potassium (K) are assumed to be used in fixed proportion to nitrogen (N).

We solve the optimization problem in eq. (2) subject to standard non-negativity constraints ($q_{mt} \geq 0$, $x_{Lmt} \geq 0$, $x_{Nmt} \geq 0$), the production technology defined by eq. (1), and an aggregate land allocation constraint:

$$\sum_{m} x_{Lmt} + x_{Lft} = b_{Lt} \tag{3}$$

where b_{Lt} is the available agricultural land base in the study region, x_{Lft} denotes land fallowed/idled. Eq. (3) ensures that the sum of land allocated by crop and rotation plus land fallowed equals the agricultural land base in each year.

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[6] Examples of unobserved factors include agronomic considerations (e.g., disease or pest control), management skill, access to capital, and risk preferences.
[7] This is a common assumption in the PMP method (Mérel and Howitt 2014).
[8] In the Lake Mendota watershed, water is not a scarce resource, thus we assume the supply of water resources is sufficient to support the cropping activities in the region, and water demand does not vary significantly across crops.

The key inputs to the calibration are aggregate land use in the catchment (i.e. acreages of crops in each rotation and acreage of fallowed land) and per acre nitrogen fertilizer applications during the reference period. Identifying crop rotations requires multiple years of remote sensing imagery and could not be identified on a year-by-year basis. Thus, our calibration model is based on a reference period identified as the average of 2003 through 2014. In other words, the calibration is based on the observed average land uses, fertilizer applications, and production levels during this reference period. In the simulation process, we simulate annual land allocations and fertilizer applications based on the time-variant crop prices.

2.2 Positive Mathematical Programming (PMP) Calibration

The objective of the PMP calibration is to solve for the values of the unknown parameters μ_m, β_{Lm}, β_{Nm}, δ_m, ρ_m, λ_{Lm}, and λ_{Nm} in equations (1) and (2) that ensure the first-order conditions for a maximum hold given observed decisions about input use and crop production. These observed decisions define the reference allocation, which includes the observed allocation of land ($\bar{x}_{Lm}$), fertilizer applications ($\bar{x}_{Nm}$) and production level ($\bar{q}_m$) at the reference period . The calibration also requires that we specify the value of the Lagrangian multiplier associated with the land constraint in eq. (3), or an initial shadow price for land, denoted $\bar{\lambda}$.[9] We also use exogenous, commodity-specific supply elasticities ($\bar{\eta}_m$) and the modeled agronomic response of crops to nitrogen fertilizer (defined as yield elasticities and denoted $\bar{y}_{Nm}$) as inputs to the calibration.

Following Mérel et al. (2013), we solve recursively for the unknown parameters in four steps. First, we independently draw 1000 values of the elasticity of substitution (σ_m) for each

[9] We calibrate the shadow price of land following Garnache et al. (2017a) by minimizing the sum of squared deviations between the modeled activities and input-level expenditures and their observed values in the baseline allocation.

crop m from a lognormal distribution with mean 1.15 and variance 0.5. We use the mean across draws in subsequent steps in the calibration.[10] In the second step, we verify that the two calibration criteria defined by Mérel et al. (2011) hold at the reference allocation. If the conditions hold, we solve for values of the parameters δ_m that ensure the supply elasticities implied by the model replicate the set of exogenous supply elasticities $\bar{\eta}_m$. In the third step, we use the calibrated values of σ_m and δ_m and the agronomic yield elasticities $\bar{y}_{Nm}$ to solve for the parameters μ_m, β_{Lm}, and β_{Nm}. With these values, we have calibrated the unknown parameters of the CES production functions in eq. (1). In the final step, we use the calibrated CES production functions and the reference land and fertilizer use to solve for the parameters λ_{Lm} and λ_{Nm} in eq. (2).

2.3 Calibration Data

We used the SAS clustering procedure FASTCLUS to generate crop rotations for the watershed based on CropScape cropland data (Boryan et al. 2011; Jiang et al. 2021). Through clustering, each pixel from remote sensing image is assigned to a crop rotation based on crop frequency. For example, a 0.5/0.5 frequency corn/soybean is assumed to represent and alternating rotation of these crops. Across all years, the three crop rotations modeled plus fallowed land, account for an average of 23.5% of the total land in the watershed.[11] Of the land we model and across years in the reference period, continuous corn (*cc*) occupies 66.5% of the land area, followed by the six-year corn-alfalfa rotation (*ca*, 23.9%), the two-year corn-soybean rotation (*cs*, 8.2%), and fallow (1.4%).

[10] Hertel et al. (1996) empirically estimate the elasticity of substitution between land and nitrogen for corn production in Indiana to be around 1.15, which we use to set the mean of the distribution for the calibration. We chose the variance to be consistent with other, similar PMP analyses (Mérel et al. 2013; Howitt 1995a; and Laborde 2011).
[11] Other land uses include grassland/pasture, developed land, open water, forest, other crops, etc.

In our model, the land allocation decision is between crop rotations, while revenue earned in eq. (2) is based on commodity production. To move between rotations and commodities, we assume land in each year is allocated in proportion to the share of each commodity within a rotation.[12] For example, one acre of land in a corn-soybean rotation produces, on average, half an acre worth of soybean yield and half an acre worth of corn yield where corn yield is specific to that following soybean. Similarly, one acre of land in the six-year corn-alfalfa rotation produces half an acre worth of alfalfa yield and half an acre of corn yield where 1/3 of the corn yield is specific to that following alfalfa by one year, 1/3 is specific to that following alfalfa by two years and the remaining 1/3 is specific to that following alfalfa by three years. Averaging in this way would be problematic if we were modeling an individual farmer's fields, which could shift from one crop to another each growing season. However, our model is one of aggregate decision making at the scale of the watershed, for which assuming average shares is reasonable. The PMP approach we take has been extensively applied, precisely for this case (Howitt 1995; Merel and Howitt 2014; Merel et al. 2014). Rather than attempting to explicitly define complex, and often unobserved, rotation constraints, the PMP calibration introduces calibrated parameters that reflect unobserved costs or benefits associated with adopting potential crop rotations. These would include, for example, the costs of switching out of a corn-alfalfa rotation and into another rotation. These costs reduce the likelihood of arbitrary rotations out of a crop and support beneficial switches into a crop. Following Merel et al. (2014), the same rationale applies for our calibration of the yield elasticities with respect to fertilizer use, which reflect unobserved costs and benefits associated with fertilizer applications for each crop rotation.

[12] The assumption aligns with our methods in identifying observed acreages of crop rotations.

We use recommended nitrogen application rates published by the University of Wisconsin Extension (2014) as the observed fertilizer applications. Among all the crops, continuous corn requires the largest nitrogen application rates, while alfalfa in the first year following corn requires the least.

Eq. (2) also includes exogenous crop prices and costs of production. Commodity prices are taken from USDA NASS survey for years 2002-2013 (NASS 2017), where we use a one-year lag in commodity prices to reflect farmers' short-run expectations over future prices at the time planting decisions are made each spring.[13] We obtain per-unit input costs for land and fertilizer for each crop and rotation from extension enterprise budgets.

For the model calibration, we need to specify supply elasticities for corn, soybeans, and alfalfa. Exact supply elasticities for our study region are not available; instead, we specify a range of values based on a summary of economic literature. We prioritize studies based on several criteria, including their geographic proximity to our study area and the recency of the estimates. The studies used and the weights for each are summarized in Supplementary Appendix Table S1. The literature yields 95% confidence intervals for the own price supply elasticities for corn, soybean and alfalfa of [0.017, 0.630], [0.067, 0.740], and [0.363, 0.633], respectively.

2.4 Agronomic Yield Response

To derive yield elasticities for use in the PMP calibration, we use the Cycles agronomic model of terrestrial nutrient dynamics, which is calibrated to reflect soil characteristics, land use, and typical agricultural management practices in the study area. Cycles is a user-friendly, multi-crop, multi-year, process-based model that simulates crop production and water, carbon and nitrogen

[13] All commodity prices are adjusted to the price level of 2010.

cycles at a daily time step. The model is an evolution of C-FARM (Kemanian and Stöckle 2010) and is closely related to CropSyst (Stöckle et al. 2014).[14]

In Cycles, hydrology is simulated using an adaptive sub-daily time step. The algorithms for heat and water transport are adapted from Campbell (1985), with reference evapotranspiration calculated using the Penman-Monteith equation. Daily plant growth is based either on radiation capture (if light limited) or on realized transpiration (if water limited), an approach that surrogates for a coupled transpiration and photosynthesis model (Kremer et al. 2008). Stomatal conductance is determined by temperature and the leaf water potential, with the latter depending on the balance of the transpiration demand, the soil water supply, and plant hydraulic properties (Camargo and Kemanian 2016; Jara and Stöckle 1999).[15] Crop development is calculated using thermal time; crop yield is calculated using the biomass accrued and a harvest index (Kemanian et al. 2007). Soil organic nitrogen and nitrogen cycling are based on saturation theory (White et al. 2014). The minimum inputs to the model are latitude, daily weather (minimum and maximum temperature, precipitation, solar radiation, dew point, and wind speed), a soil description (layer thickness, clay, sand and organic matter content), a cropping sequence, and agricultural management practices. Cycles simulates perturbations of biogeochemical processes caused by agronomic practices such as tillage, irrigation, organic and inorganic nutrient applications, annual and perennial crop selection, and grain and forage harvest.

For each crop, we use Cycles to simulate watershed level yield responses for corn by rotation and year under a range of nitrogen application rates, ranging from 0 to 178 pounds per acre.[16] We estimate the yield response of corn to nitrogen fertilizer applications by fitting a

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[14] For these simulations, we used Cycles version 0.5.0-alpha.

[15] Stomatal conductance is a measure of the exchange of water vapor between a plant and the atmosphere.

[16] When applying the Cycles model, we use machine learning models to generate regional level yield responses without using soil information. Yield does vary with many factors, from intrinsic soil features, presence/absence of

Mitscherlich-Baule function for corn within each crop rotation. This functional form is often used to fit yield data because it captures a growth plateau in the fertilizer-yield relationship and allows for factor substitution in crop production (Frank et al. 1990). Nitrogen fertilizer has a negligible effect on the yields of nitrogen-fixing soybeans and alfalfa; the yields of these crops vary annually due to weather but are invariant to fertilizer inputs.

For the nitrogen application rate, *N*, the per-acre yield for crop *m* at year *t* (y_{mt}) is given by:

$$y_{mt} = \begin{cases} \alpha_{m0}\left(1 + \boldsymbol{\gamma_{mt}}\boldsymbol{T} - \exp\left(-\alpha_{m1} * (\alpha_{m2} + N)\right)\right) + \varepsilon_{mt} & if\ m = cc - c, cs - c, ca - c1, ca - c2, ca - c3 \\ \tau_{mt} & if\ m = cs - s, ca - a1, ca - a2, ca - a3 \end{cases} \quad (4)$$

where $\boldsymbol{T}$ is a matrix of year-specific dummy variables, and $\alpha_{m0}, \boldsymbol{\gamma_{mt}}, \alpha_{m1}, \alpha_{m2}$ are parameters characterizing the shape of the yield function. The parameter α_{m0} represents the average plateau for growth in the long run, $\boldsymbol{\gamma_{mt}}$ represents the year-specific plateau premium due to varying weather conditions, α_{m1} captures the average influence of nitrogen applications in the long run, and α_{m2} captures the effect of natural factor endowments, such as soil and water. In the second line of eq. (4), τ_{mt} represents yield for soybeans and alfalfa.

Using the predicted yields by year and fertilizer application level produced by Cycles, we estimate the parameters of the yield functions in eq. (4) using nonlinear least squares. Based on the estimated parameters, we also calculate the average yield responses for the reference period.

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tile drains, operational features, and crop rotations. However, recent studies indicate that interannual variation of climate variables (e.g., temperature and precipitation) are more important (Schlenker and Roberts, 2009; Huffman et al.,2020). The fact we can model yields with machine learning models without using any soil information indicates that a lot of the relevant variation is elsewhere (such as climate factors) because agricultural soils are already mostly selected for crop production. Thus, doing a field-by-field analysis will not add too much information to the yield responses.

Fig. 3 plots Cycles yield against nitrogen fertilizer applications at the reference period, along with our fitted Mitscherlich-Baule yield function. The estimated yield curves fit the Cycles yield simulation data well, with an R^2 larger than 0.98 for all crops in our model.

Following Mérel et al. (2013), we use eq. (4) to define the elasticity of crop yield with respect to fertilizer applications at the recommended level of nitrogen fertilizer applications ($\bar{a}_{Nm}$) and the reference yield for crop *m* ($\bar{y}_m$). The yield elasticity by crop is given by:

$$\bar{y}_{Nm} = \begin{cases} \dfrac{\alpha_{m0}\alpha_{m1}\exp(-\alpha_{m1}(\alpha_{m2}+\bar{a}_{Nm}))\,\bar{a}_{Nm}}{\bar{y}_m} & if\ m = cc-c, cs-c, ca-c1, ca-c2, ca-c3 \\ 0 & if\ m = cs-s, ca-a1, ca-a2, ca-a3 \end{cases} \quad (5)$$

The reference yield elasticity calculated in eq. (5) is used in the PMP calibration to ensure that the modeled yield elasticities replicate the simulated agronomic responses of crop and at the observed level of fertilizer applications.[17]

2.5 Leaching and Emission Responses

In the simulation process, we simulate annual farmer decision in terms of land and fertilizer use based on changing commodity prices, then we quantity nitrate leaching and nitrous oxide emissions using Cycles outputs. For each simulation used to fit eq. (4) based on unique combinations of weather conditions, crop rotation, and nitrogen fertilizer application rate—we use Cycles to simulate nitrate leaching and nitrous oxide emissions for a growing season.[18,19] We use the resulting dataset of simulations to fit production functions for leaching and emissions.

$$e_{mtn} = \begin{cases} \varphi_{m0tn} + \varphi_{m1tn}N + \varphi_{m2tn}N^2 & if\ m = cc-c, cs-c, ca-c1, ca-c2, ca-c3 \\ 0 & if\ m = cs-s, ca-a1, ca-a2, ca-a3 \end{cases} \quad (6)$$

[17] Yields at observed levels are calculated using observed nitrogen application levels and our calibrated biophysical nitrogen response functions in equation (4).

[18] Cycles simulates leaching and emissions at a daily time step, capturing the importance of precipitation patterns relative to the timing of fertilizer applications in determining nitrogen losses. We aggregate to obtain leaching and emissions totals over the extent of each growing season.

[19] Our simulated years cover a broad range of weather conditions, including wet, dry, and normal years. We report the precipitation levels of growing seasons in Table S10.

For each crop *m* in year *t*, we estimate the following model using ordinary least squares: where *n* indexes the externality ($n = leaching, emissions$), e_{mtn} is the per-acre externality produced, *N* denotes the nitrogen application rate, and $\varphi_{m0tn}, \varphi_{m1tn}, \varphi_{m2tn}$ are parameters. Soybeans and alfalfa, which do not benefit from supplementary nitrogen fertilizer, do not contribute significantly to nitrate leaching or nitrous oxide emissions. Detailed coefficient estimates are reported in the Supplementary Appendix. The functional form fits the simulation data well for both externalities, with an average R^2 of 0.98 across crops.

Using the regression results for eq. (6), we predict leaching and emissions per unit of land area at the simulated level of fertilizer applications as:

$$\hat{e}_{mtn}(k_{Nmt}) = \hat{\varphi}_{m0tn} + \hat{\varphi}_{m1tn} k_{Nmt} + \hat{\varphi}_{m2tn}(k_{Nmt})^2 \quad (7)$$

where k_{Nmt} is the simulated per-acre level of nitrogen applications from the calibrated economic optimization model, and $\hat{\varphi}_{m0tn}$, $\hat{\varphi}_{m1tn}$, and $\hat{\varphi}_{m2tn}$ are parameter estimates for eq. (6). Finally, we obtain aggregate leaching and emissions for the region (E_{tn}) as:

$$E_{tn} = \sum_m \hat{e}_{mtn}(k_{Nmt}) k_{Lmt} \quad (8)$$

Where k_{Lmt} is the optimal allocation of land to each crop from the calibrated economic optimization model.

2.6 Social Costs of Nitrogen and Benefit-Cost Analysis

Within the calibrated economic optimization model, we impose a series of increasingly stringent nitrate leaching constraints, ranging from a 5% to 95% reduction in leaching relative to the status quo. Let $\tilde{E}_{t,leaching}$ denote the status quo level of nitrogen leaching. The constraints are of the form:

$$E_{t,leaching} \leq (1 - \theta)\tilde{E}_{t,leaching} \quad (9)$$

where θ is the proportional reduction in leaching. The modeling constraint is on nitrate leaching only; because of jointness in the production of externalities, the leaching constraints imply a change in nitrous oxide emissions. This also mimics current policies that target reductions in nitrate leaching and here we are demonstrating the nitrous oxide co-benefits. We compute the reduction in nitrous oxide emissions associated with each leaching constraint as

$$\Delta E_{t,emissions}(\theta) = E_{t,emissions}(\theta) - E_{t,emissions}(0) \quad (10)$$

where $E_{t,emissions}(0)$ is the emissions level associated with the status quo and $E_{t,emissions}(\theta)$ is the level of emissions associated with leaching reduction constraint θ.

To quantify the monetary values of reduced leaching and emissions, we use the social cost of nitrogen, which reflects the present value of monetary damages caused by a unit increase in nitrogen pollution. The method of Keeler et al. (2016) is applied to calculate the social costs of nitrate leaching and nitrous oxide emissions for the Lake Mendota Watershed.

The social costs of nitrate leaching are calculated based on the costs associated with groundwater $NO3-$ contamination in two sources (private drinking wells and public water supplies) and the percentage of population served in each water source. We estimated the total costs with $NO3-$ contamination in private wells based on county-level replacement costs developed by the Wisconsin Department of Natural Resources, which are then scaled to the Lake Mendota watershed using the number of private wells and the percentage of wells over the 10 ppm nitrate-N standard (Wisconsin GCC, 2021). The net present annual value was calculated assuming a 20-year time horizon and a 3% discount rate. Using modeling results in equation (8), we calculate average annual nitrate leaching at the baseline, then we converted the net present annual costs into per-unit costs of nitrate leaching by dividing the annual costs of Lake Mendota watershed by average annual nitrate leaching. The estimated total costs of public water supplies come from the nitrate treatment costs. Industry standards for treatment are similar across the nation, so we used the net present value per household from Minnesota and scaled the value for the Lake Mendota watershed based on the number of people served by municipal providers within the watershed.[20,21]

The social costs of nitrous oxide emissions are calculated based on the social costs of carbon dioxide (\$0.025/kg CO2 emitted under a 3% discount rate) and reflect the global warming potential of nitrous oxide (273 times of CO2).

Accordingly, the average social costs associated with per pound of nitrate leaching is \$0.29 with a range from \$0.22 to \$0.36, and the average social costs associated with per pound nitrous oxide emissions is \$6.8. The total social costs associated with each form of pollution and under each policy scenario is:

$$TSC_{tn}(\theta) = SC_n * E_{tn}(\theta) \tag{11}$$

where TSC_{tn} denotes the total social costs from externality *n* in year *t* with leaching constraint θ; SC_n is the social cost per pound arising from externality *n*, and $E_{tn}(\theta)$ is the regional level of externality with leaching reduction constraint θ. The benefit from imposing a nitrate leaching constraint, evaluated relative to the status quo, is given by:

$$B_{tn}(\theta) = TSC_{tn}(0) - TSC_{tn}(\theta) \tag{12}$$

where $TSC_{tn}(0)$ are total social costs under the status quo and $TSC_{tn}(\theta)$ are total social costs under leaching constraint θ.

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[20] Costs associated with nitrate treatment for public water suppliers in Minnesota are reported in table S3 of Keeler et al. (2016), due to the lack of treatment costs for Lake Mendota watershed, we calculate the mean value and 95% confidence interval based on the net present value per household of Minnesota and reported a range of values in the following calculation.

[21] Number of people served by Lake Mendota is calculated based on the wells data and information of public water system retrieved from groundwater retrieval network of Wisconsin DNR.

Policy analysis often relies on a benefit-cost ratio to summarize the overall relationship between the costs and benefits of a proposed project, which serves as a basis for adopting or rejecting a particular policy. Here, we examine how the benefit-cost ratio changes with the inclusion of co-benefits from nitrous oxide emissions. The cost of imposing a leaching constraint, θ, is the change in net revenues to farmers due to changes in input use and crop production that arise from meeting the constraint. Let $NR_t(\theta)$ denote net revenue earned by all farmers in the region in year *t* when leaching constraint θ applies:

$$NR_t(\theta) = \sum_m \{p_{mt}\tilde{q}_{mt}(\theta) - [(c_{Lm} + \tilde{\lambda}_{Lm})k_{Lmt}(\theta) + (c_{Nm} + \tilde{\lambda}_{Nm})k_{Nmt}(\theta)]\} \qquad (13)$$

Eq. (13) makes explicit the dependence of the optimal levels of production $\tilde{q}_{mt}$ and input use on the leaching constraint. The parameters for the CES production function and the shadow costs of land ($\tilde{\lambda}_{Lm}$) and nitrogen ($\tilde{\lambda}_{Nm}$) are calibrated using the status quo land allocation and do not depend on θ. The cost of imposing a nitrate leaching constraint, evaluated relative to the status quo, is given by:

$$C_t(\theta) = NR_t(0) - NR_t(\theta) \qquad (14)$$

where $NR_t(0)$ is net revenue under the status quo and $NR_t(\theta)$ is net revenue under leaching constraint θ.

Using eq. (12) and eq. (14), we calculate the benefit-cost ratio without nitrous oxide emission co-benefits as:

$$R_{to}(\theta) = \frac{B_{t,leaching}(\theta)}{C_t(\theta)} \qquad (15a)$$

and the benefit-cost ratio with nitrous oxide emission co-benefits as:

$$R_{tc}(\theta) = \frac{\sum_n B_{tn}(\theta)}{C_t(\theta)} \qquad (15b)$$

where the numerator in (15b) sums benefits across both externalities. We calculate the benefit-cost ratio for each year *t* and for each leaching constraint θ.

3. Results

We first report and interpret the results from the PMP calibration described in section 2.2 along with the simulation results under the status quo. We then present the simulation results for a series of progressively stringent nitrate leaching constraints in 5% increments, as defined in eq. (9).[22] Finally, we describe the benefits of leaching and emission reductions and examine the effects of including co-benefits in the calculation of the benefit-cost ratio for each policy scenario.

3.1 Model Calibration and Status Quo

The calibrated values for the unknown parameters in equations (1) and (2) are reported in Table 1. Here, we focus on interpreting the calibrated shadow costs for land and nitrogen fertilizer for each commodity and rotation ($\tilde{\lambda}_{Lm}$ and $\tilde{\lambda}_{Nm}$). These parameters represent the adjustment to input costs needed to rationalize observed decision making at observed commodity and input prices.

For all commodity-rotation combinations, the PMP calibration yields negative values for $\tilde{\lambda}_{Lm}$, which indicates that there are unobserved benefits to using the land for the purpose of agricultural production. For nitrogen fertilizer, we observe negative values for $\tilde{\lambda}_{Nm}$ for corn in all rotations, suggesting that there are unobserved benefits from fertilizer applications on corn. For corn grown within the corn-soybean and corn-alfalfa rotations, our results indicate a large hidden benefit. Furthermore, as indicated in Table 1, the magnitude of this unobserved benefit is large

[22] We assume the regulator has complete information about the amount of nitrate leaching associated with production practices and can implement leaching reduction caps throughout the watershed.

enough that it offsets most of the observed per-unit nitrogen fertilizer costs. At observed market prices, farmers in our study region apply nitrogen more than the optimal nitrogen application level suggested by the yield response function (Figure 3). Farmers may overapply fertilizer because it is a relatively inexpensive input and guards against downside variability in yield.[23]

Using our calibrated parameters and equation (2), we simulate land use and fertilizer decisions for each year, then using the fitted leaching and emission functions to compute annual leaching and emission levels at the status quo (Fig. 4). In the status quo (Fig. 4a), the largest amount of acreage is allocated to the continuous corn rotation, which also has the greatest per-acre levels of nitrogen applications. As a result, the continuous corn rotation contributes the greatest to leaching and emissions, followed by the corn-alfalfa rotation, and the corn-soybean rotation. The simulations from Cycles indicate that leaching and emissions vary considerably across years: 2010, the peak leaching year, had leaching six times larger than 2003 with the lowest leaching. The quantity of leaching is mainly driven by the timing and magnitude of precipitation events relative to the timing of fertilizer applications. For instance, during growing seasons (April to October), the average monthly precipitation is 4.55 inches in year 2008, 3.80 inches in year 2009, 5.14 inches in year 2010, thus we could observe the leaching drops in 2009 and spikes in 2010. Emissions of nitrous oxide, on the other hand, are not driven by sporadic precipitation events. As a result, the interannual variance in nitrous oxide emissions is smaller than the variance in leaching.

It is worth noting that none of the changes in crop rotations in our simulation violate key rotational constraints. For example, when decreasing land in the corn-alfalfa rotation, farmers would never take land out of the first year of alfalfa or the second year of alfalfa due to the costs

[23] Excess fertilizer may be applied as a hedge against weather, agronomic, or economic risk, which farmers do not know in advance (Ji and Cobourn 2020; Paudel and Crago 2019; Stuart et al. 2014).

of the foregone benefits. They could, however, decide to change the rotation in any of the three corn years or the third year of alfalfa. This implies that four-sixths of the land in the corn-alfalfa rotation is available for an "exit" into another rotation in any given year. Consider 2006 as an example, a total of 24,208 acres was in the corn-alfalfa rotation. This means that no more than 16,139 acres could change to another rotation. This is more than adequate to accommodate the largest change in this rotation, 10,404 acres, within our simulation. An aggregate rotation constraint therefore is not binding.

It is true that this makes it difficult to fully capture changes in leaching at each individual field due to the history of cropping decisions on that land. For example, when land is shifted into a continuous corn rotation, it is possible that some acreage comes out of the corn year in the corn-soy rotation, the soybean year in the corn-soy rotation, the three corn years in the corn-alfalfa rotation, or the third year of alfalfa in the corn-alfalfa rotation. Of these possibilities, the recommended fertilizer application rate for corn following any corn year as well as the third year of alfalfa is similar (166 lbs/acre) and the recommended fertilizer application rate for corn following soybeans is 115 lbs/acre. Given our results, it is most likely that land came out of the eligible years in the corn-alfalfa rotation, for which the same recommended fertilizer application rates apply as for continuous corn.

As a worst-case scenario, if we assume that all the land added to continuous corn in 2007 came out of land in a corn-soybean rotation the preceding year (1/2 of which would have been in soybeans), we would overstate the amount of fertilizer applied by 3.4% of the baseline quantity of fertilizer applications to continuous corn in 2007. A similar result, though smaller in magnitude, holds for 2011, the year with the second greatest increase in continuous corn. This overestimate of fertilizer applications could be problematic to our overall results if it coincided with the years in which we observe the highest level of leaching or emissions. However, neither 2007 nor 2011 was the year with the highest leaching, nor the highest level of emissions. The production of leaching and emissions is far more sensitive to precipitation than to changes in fertilizer applications at the intensive margin. Thus, even if we were to adjust downward the amount of fertilizer applied to continuous corn to capture the benefits of following soybeans, the adjustment would have a negligible effect on year-to-year differences in leaching and emissions externalities, as well as the estimated co-benefits from their reduction.

3.2 Nitrate Leaching Policy Scenarios

We now turn to farmers' behavioral adjustments under the nitrate leaching constraints. To meet leaching targets, farmers adjust along the intensive margin, by altering per-acre nitrogen fertilizer applications, and/or along the extensive margin, by reallocating land among crop rotations and fallow land. The relative importance of the intensive margin effect and the extensive margin effect depends on the policy stringency and the tradeoff between profits and environmental targets. For relatively small reductions in leaching, we observe changes primarily along the intensive margin (see corn-soybean and corn-alfalfa rotations in Figure 5a). As the leaching constraint becomes more stringent, we observe a greater reliance on adjustments along the extensive margin (decrease in corn rotation acreages and an increase in fallow land in Figure 5b). The box plots display the distribution of the results driven by interannual differences in crop prices and weather conditions.

When leaching policy targets 25% or less reduction, we find significant reductions in per-acre nitrogen application levels for the corn-soybean and corn-alfalfa rotations but slight changes for continuous corn rotation (Figure 5(a)). The reductions of per-acre nitrogen applications are due to the increase of farm profits. This farm benefit arises because crops are currently overfertilized, as shown by the flat areas in the response functions presented in Figure 3. Farmers can reduce their applications of nitrogen, especially on the corn-soybean and corn-alfalfa rotations, without seeing significant yield reductions. As a result, farmers can achieve small leaching targets at the intensive margin without a loss in profits. The return of N application is high on continuous corn rotation, thus the N application rates on continuous corn rotation is relatively stable.

We observe an increase of acreages in the corn-soybean rotation and decreases of acreages of continuous corn and corn-alfalfa rotation when leaching policies are 25% or less (Figure 5(b)). According to agronomic information, even if the N application is zero, leaching will always exist as there is endogenous N mineralizing. The non-zero leaching is low for continuous corn and corn-soybean rotation but will exaggerate in the corn alfalfa rotation. Alfalfa fixes nitrogen from the atmosphere and when alfalfa residues decompose, they can mineralize nitrogen. Thus, for the corn-alfalfa rotation, although reducing nitrogen applications might be profitable at small reductions, the corn-alfalfa rotation acreage declines due to N mineralizing.

As the stringency of the leaching cap increases over 30%, intensive margin adjustments alone cannot ensure the leaching constraint is met. The only way to achieve the target is to move land out of crop production and into fallow. Starting at a leaching reduction of 30%, we observe substantial increases in fallow/idled land; with a 95% reduction, farmers fallow 60% of the land base, which is likely an unpopular policy that will not be viable without substantial farmer compensation.

Despite differences in the peak years and variances across years of nitrate leaching and nitrous oxide emissions, reductions in nitrous oxide emissions are positively correlated and proportional to reductions in nitrate leaching. This follows from behavioral adjustments, primarily changes in the land allocated to the continuous corn rotation. When leaching falls by 10%, emissions decline by 11%; when leaching falls by 90%, emissions decline by 85%.

3.3 Emissions Co-benefits

Table 2 reports nitrate leaching reductions and the nitrous oxide co-benefit emission reductions, in aggregate across crop rotations and years; Figure 6 illustrates the distribution of results across years within the simulation and the results broken out for each crop rotation.[24] Due to interannual variability in crop prices and weather conditions, the absolute amount of leaching and nitrous oxide reductions differ across years. The largest interannual variation comes from continuous corn rotation.

Table 2 also reports the monetary benefits of nitrate leaching reductions and nitrous oxide co-benefit emission reductions, in aggregate across crop rotations and years; Figure 7 illustrates the distribution of monetary benefits across years. Monetary benefits increase when the regulation become more stringent, whereas the interannual variability comes from the interannual variability in nitrous oxide reductions. When On average, for a 30% leaching reduction, we find that emission co-benefits amount to $ 194,600 per year with a farmer cost of $482,810. As a point of comparison, this benefit amounts to approximately 26% of the 2019 (annual) budget set by Dane County to convert lands at greatest risk of runoff from agriculture into prairie and grasses.[25]

The economic benefits of reducing nitrate leaching are generally small, compared with the economic benefits of reducing nitrous oxide emissions, which is not surprising. The benefits

[24] In Table 2, we calculate the benefits of nitrate leaching reductions based on the average social costs of nitrate leached, which is $0.29/lb. Lower bounds and upper bounds of benefits are reported in Table S9 based on the lower and upper estimates of the social costs of nitrate leached.

[25] According to Clean Lake Alliance, in year 2019, Dane County budgeted $750,000 for land conversion.

of reduced greenhouse gas emissions accrue more broadly—at a global scale—than do the social benefits from improvements in water quality in a watershed, which are more localized. This result highlights the missing categories of benefits in assessments of water quality policies noted by Keiser et al. (2019). For example, according to Keiser and Shapiro (2019), the estimated average benefit-to-cost ratio of the Clean Water Act is 0.24 implying costs exceed benefits.

In our analysis, the benefit-cost ratios for nitrogen constraints of 30% or more are positive, yet less than 1.0, indicating that farmer costs exceed social benefits. However, simply looking at the magnitude of these ratios misses the important story of our results. When co-benefits are included for the 30% constraint the benefit-cost ratio increase from 0.07 to 0.48, an almost 7-fold increase, which highlights the importance of co-benefits. The question that follows is what will happen to the benefit-cost ratios if other co-benefits are added such as wildlife habitat provide to migratory birds from the fallow land (e.g., Paterson and Best 1996; Best et al. 1997; Sample 1997).

4. Discussion and Conclusion

By integrating economic and agronomic models, we propose a modeling framework that illustrate the linkage between biophysical process of nitrogen cycling and farmer decision making. We use the model to simulate the joint production of nitrate and nitrous oxide as a function of farmer decisions at the extensive margin and at the intensive margin and quantify the environmental and economic impacts of progressively stringent reductions in nitrate leaching. Our model results highlight that the co-benefits from nitrous oxide abatement are substantial and their inclusion increase the benefit-cost ratio of water quality policies. In this section, we highlight our implications for the effectiveness of water policies, the adoption of best management practices, and the implementation of climate smart agriculture.

Regulating nonpoint pollution is a challenging issue for policymakers. The difficulties involve the lack of enforceable standards for such non-point pollution, and the complexity in modeling the production relationship between nutrient inputs and the biophysical process that led to leaching (Kling 2011). An important advantage of our integrated modeling is the ability to predict the effect of "what if" scenarios while capturing the feedback between farmer decision making and the biophysical process. The progressively stringent leaching constraints imposed cover a wide range of potential changes in water quality targets and provide reference bounds to inform potential policy actions. Our results suggest that the stringency of the leaching reduction target affects the behavioral adjustments made by farmers as they adjust their nitrogen fertilizer and land allocation decisions. For example, for small reductions, policies to manage nitrogen-related pollution from agriculture, policies incentivizing reduced fertilizer application rates at the intensive margin may be appropriate. Since we find that farmers are overapplying fertilizer, a first step may be enhancing education on the crop-yield benefits of fertilizer applications and the social cost to their communities from over application, thereby encouraging better management practice (Laboski et al., 2006). Greater reductions in agricultural pollution will require action at the extensive margin beyond adjustments in fertilizer use. For example, land-use conversion or retirement programs that compensate farmers may be required to achieve significant reductions in leaching. Understanding these responses by farmers can help policymakers to choose effective policy instruments to achieve the desired reduction in leaching.

In addition, the results highlight that the co-benefits from nitrous oxide abatement are substantial, and their inclusion increases the benefit-cost ratio. The benefits of reduced greenhouse gas emissions accrue more broadly—at a global scale—than do the social benefits from improvements in water quality in a watershed, which are more localized. Making decisions about the adoption and design of policies to avoid the negative impacts of nitrogen fertilizers, without considering such co-benefits, can lead to socially-inefficient outcomes. In terms of production patterns, ignoring co-benefits results in too great an allocation of land to crop production, particularly a corn monoculture and too high a rate of nitrogen fertilizer applications.

Due to the stochastic feature of nonpoint source pollution and the difficulty in observing pollution at the farm level, voluntary adoption of best management practices (BMPs) has been widely used to achieve water quality goals (Rabotyagov et al. 2014). However, the low adoption rate of BMPs remains a challenging question for policymakers even as a large suite of federal and state programs has been developed (Yehouenou et al. 2020). This policy failure occurs because the private costs of reduction in nitrate leaching reduction are borne by farmers, whereas the co-benefits of reduced nitrous oxide emissions (i.e., reduced social costs) accrue to the broad public.

There are BMPs, such as riparian buffer restoration, which can potentially reduce nutrient pollution while also sequestering greenhouse gases. If these co-benefits are considered, and a mechanism is established to compensate farmers for emissions reductions, farmers could see economic benefits from adopting environmentally friendly practices. For example, additional incentives could arise from selling carbon offsets on the climate exchange market, which could boost the adoption of BMPs to achieve water-quality improvements (Gasper et al. 2012).

Co-benefits from GHG emissions is one example of the “missing” benefits of water policies as indicated in Keiser et al. (2019). The production of water quality benefits is joint with the production of a myriad of other environmental benefits, including not only climate change mitigation, but also water quantity, terrestrial and aquatic habitat, biodiversity, and human health effects (Kroetz et al. 2020; Rabotyagov et al. 2014; Sample 1997; Olmstead 2010). As part of the process of recognizing and quantifying these co-benefits, an understanding of the relationship between agricultural processes and complex ecosystems is important when designing policy instruments to meet environmental objectives.

Support of climate-friendly practices (e.g., cover crops, low/no-till, nutrient management) is highlighted in the U.S. Department of Agriculture's climate-smart agriculture program. Many climate-friendly practices are also water friendly. Thinking from the other side, co-benefits of water pollution reduction would exist in the climate change policies. Considering the joint production of water and climate benefits, quantifying both climate and water benefits is essential and helps to avoid biased benefit estimates if both were modeled separately. In the future, more integrated modeling of air and water pollutants via collaborations between agronomists and economists is critical for successfully modeling agri-environment systems.

It is worth noting several limitations of our study. First, in our analysis, we impose a command-and-control policy whereby the policy makers set the edge-of-field water quality goals in identifying the desired abatement actions. Although edge-of-field monitoring is possible, it is not popular in the implementation of water policies. Currently, nonpoint source pollution is not directly regulated under Clean Water Act. Instead, state governments rely on Total Maximum Daily Load (TMDL) to address water-quality issues for impaired water bodies. For future analysis, we suggest an extension of our modeling framework to couple with a hydrologic-solute transport model (such as the Penn State Integrated Hydrologic Model) and a limnology model (such as the General Lake Model model) to capture the fate and transport of nitrate and quantify changes in watershed-scale nitrate loadings (Cobourn et al. 2018). Second, in the calculation of monetary values of nitrogen leaching, we only considered damage costs of groundwater contamination, which excludes other important damage categories such as eutrophication and underestimates the marginal damages associated with nitrogen leaching. A more comprehensive valuation analysis could be done in the future to account for the different categories of damages. For example, our model could be linked to the framework proposed by Weng et al. (2020), in which the General Lake Model, which accounts for eutrophication, is linked with a hedonic property value model that considers one aspect of the social cost of eutrophication. Third, we chose to model 5% to 95% reductions to cover a wide range of potential changes in water quality targets. Although we could demonstrate the results up to a 95% reduction using our integrated assessment model, in practice, there are many uncontrolled variables and policy uncertainties that would make high percentage reductions hard to achieve. Providing incremental simulations over the range allows for consideration of potential co-benefits as actual targets are considered in policy discussions. Last, the social cost of nitrogen and the effectiveness of water policies are inherently watershed specific. The social costs of nitrogen depending on the N form, the location and transport of N, and the vulnerability of the local communities (Keeler et al. 2016). The effectiveness of water policies depends on a bundle of natural factors such as watershed characteristics as well as social factors such as land use and economic development patterns (Langpap et al. 2008, Rabotyagov et al. 2014). Our coupling framework demonstrates the importance of considering co-benefits in other watersheds as well as providing a framework for investigating co-benefits in the watersheds.

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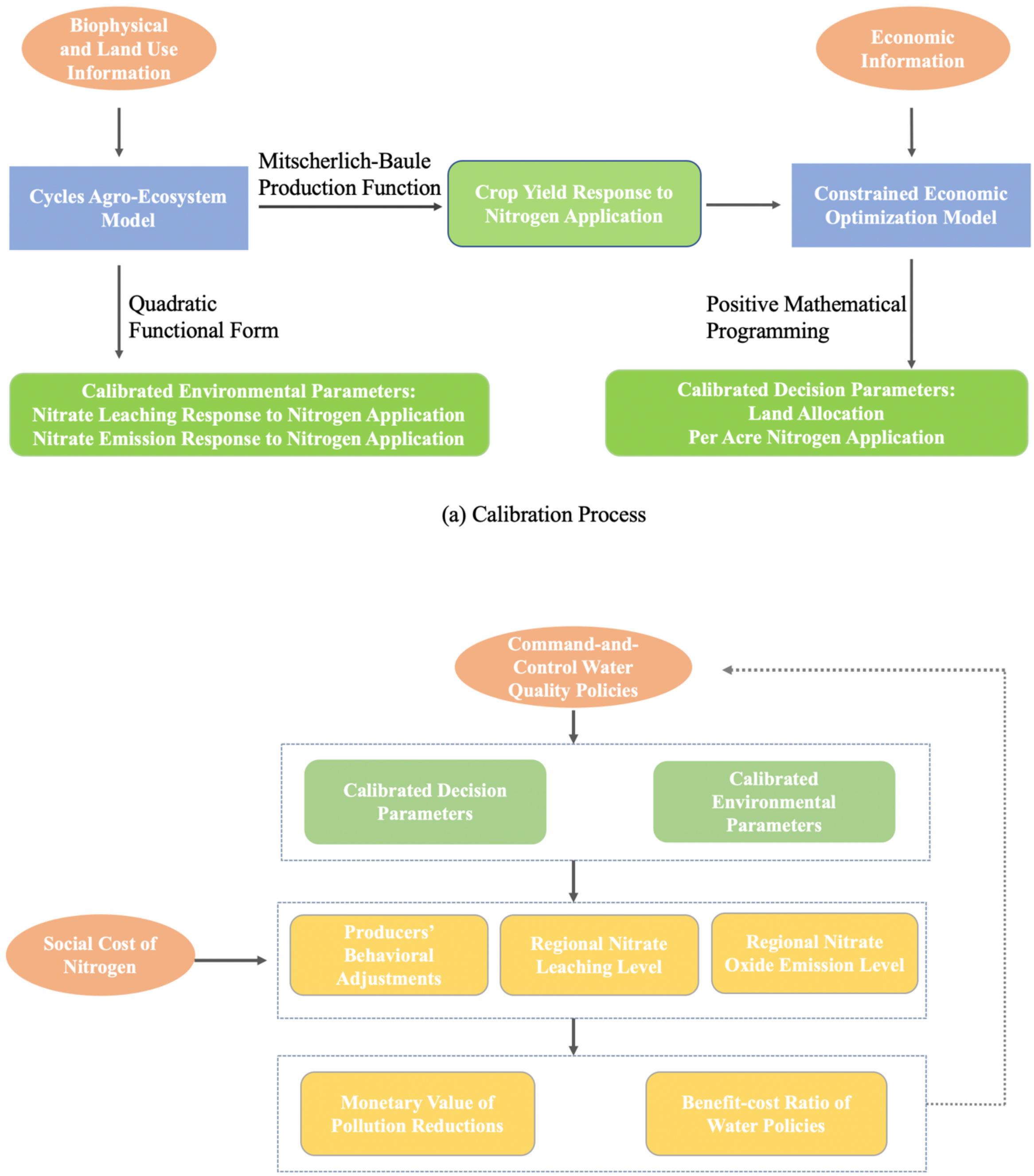


(b) Policy Simulation Process

Figure 1. Integrated Assessment Modeling Framework

Notes: The integrated assessment model consists of a calibration process (panel a) and a policy simulation process (panel b). Red circles indicate model inputs, blue boxes indicate specific models, green boxes indicate outputs from the calibration process, yellow boxes indicate outputs from the policy simulation process.

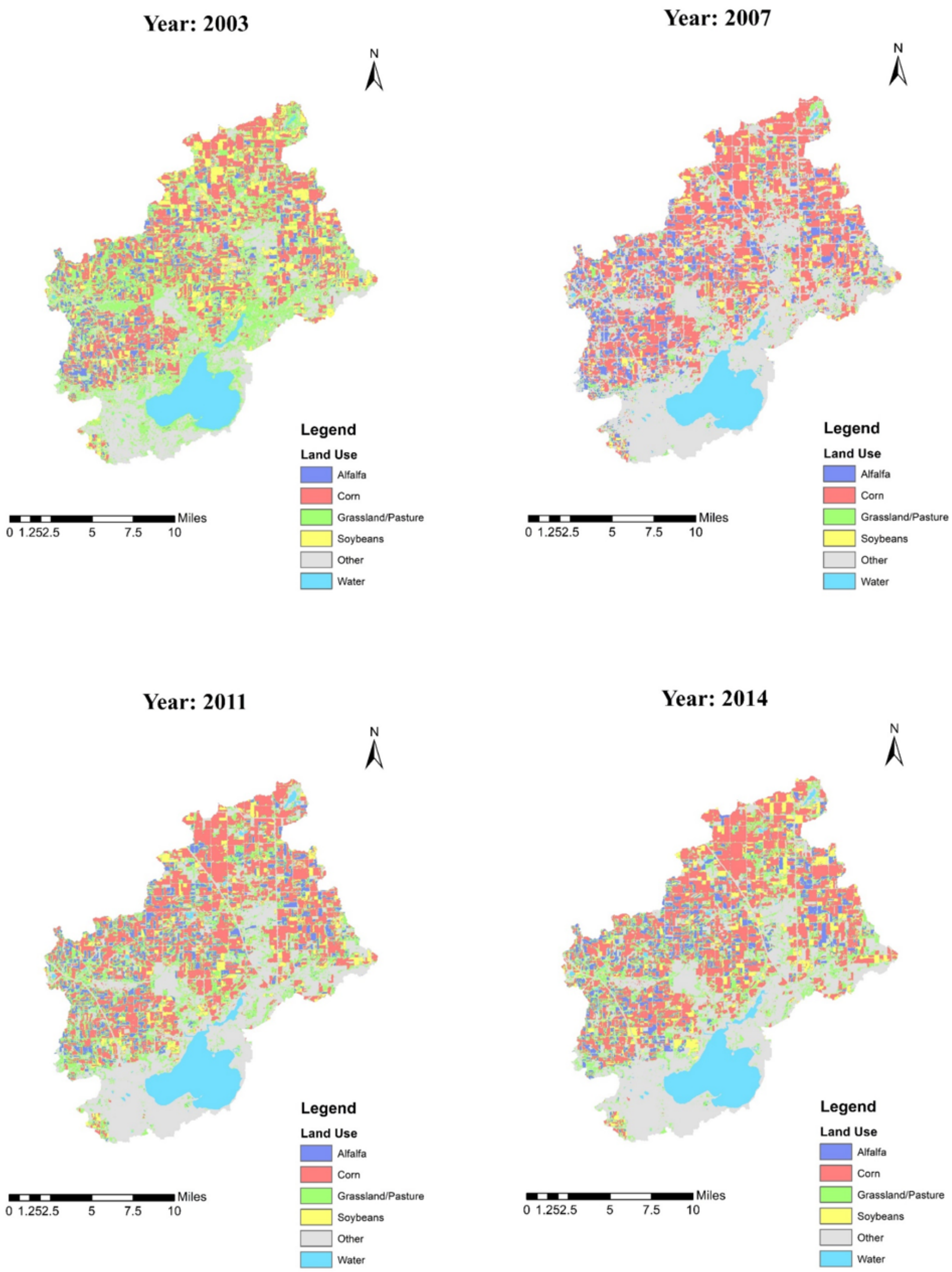


Figure 2. Agricultural Land Use in the Lake Mendota Watershed, Wisconsin, USA

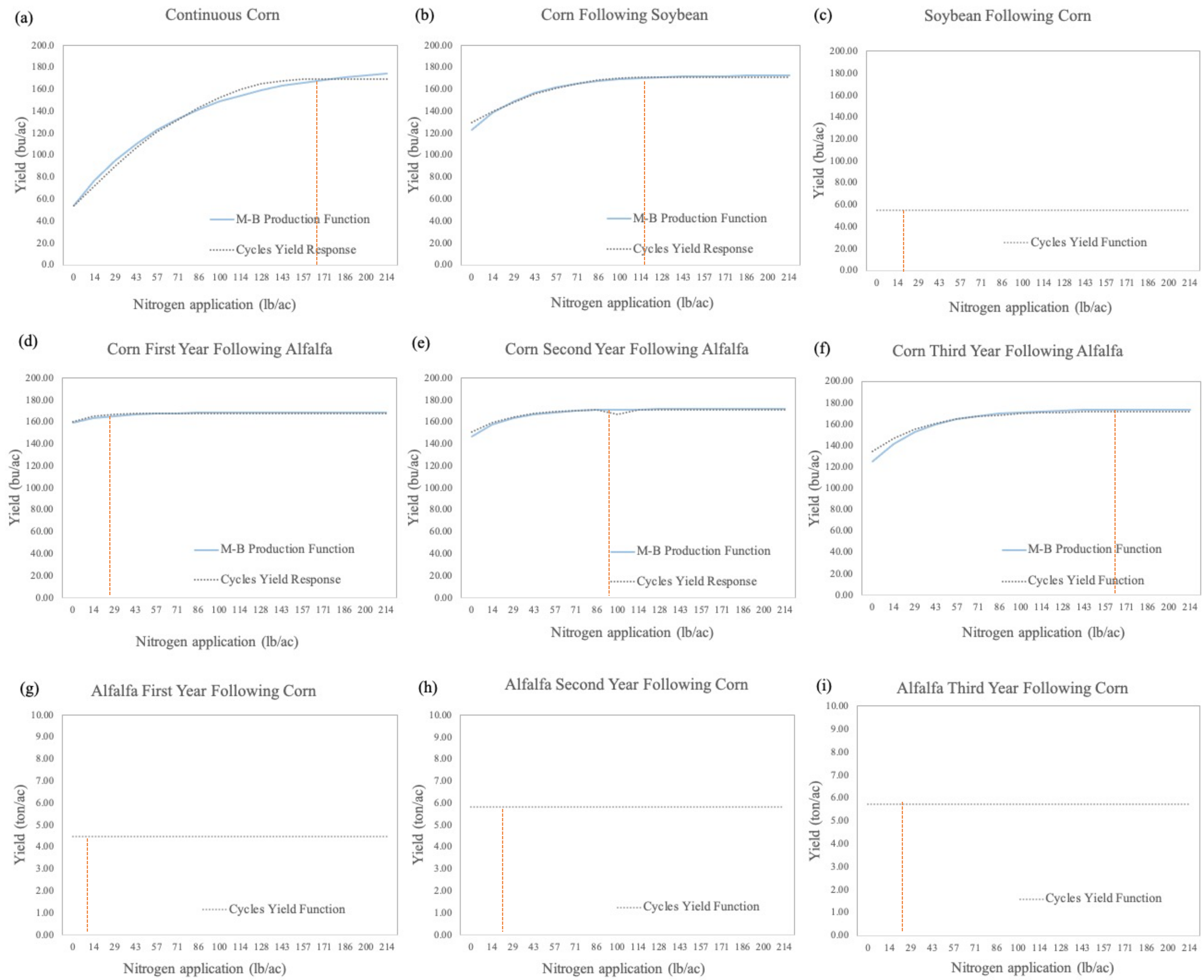


Figure 3. Per-acre Yield Response to Nitrogen Fertilizer Applications, by Commodity and Rotation

Note: The dashed orange lines indicate the observed fertilizer application levels for PMP calibration.

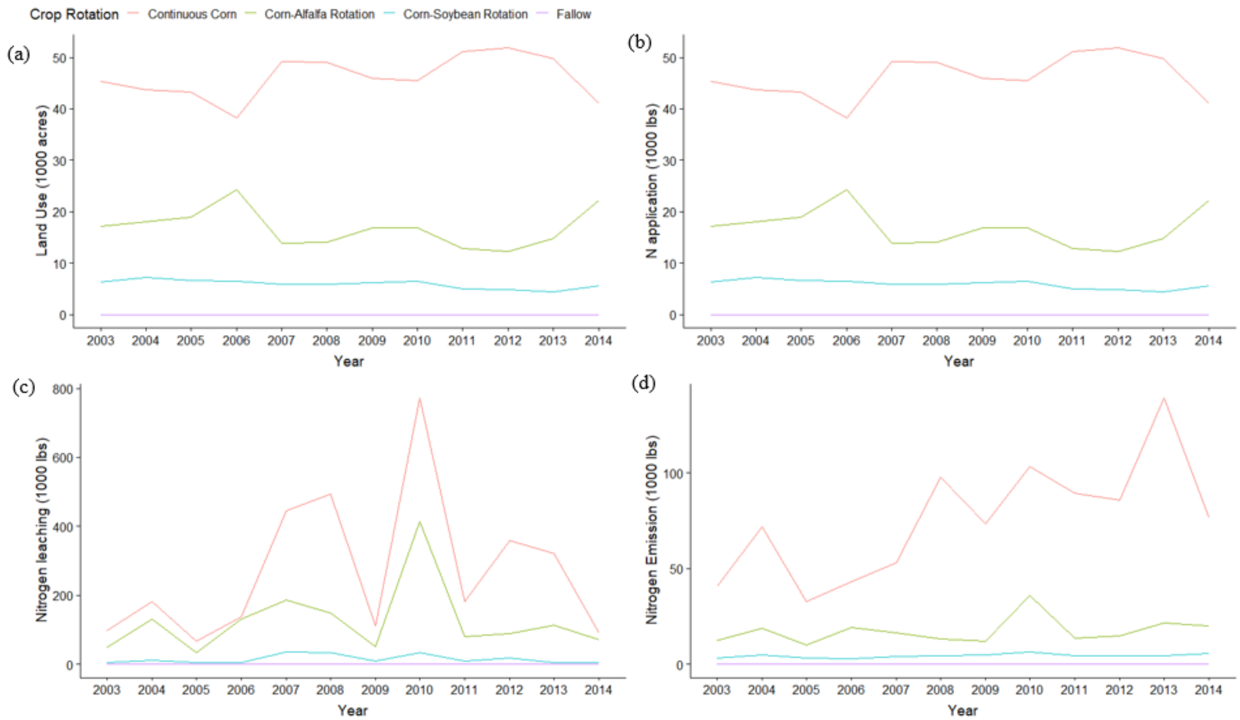
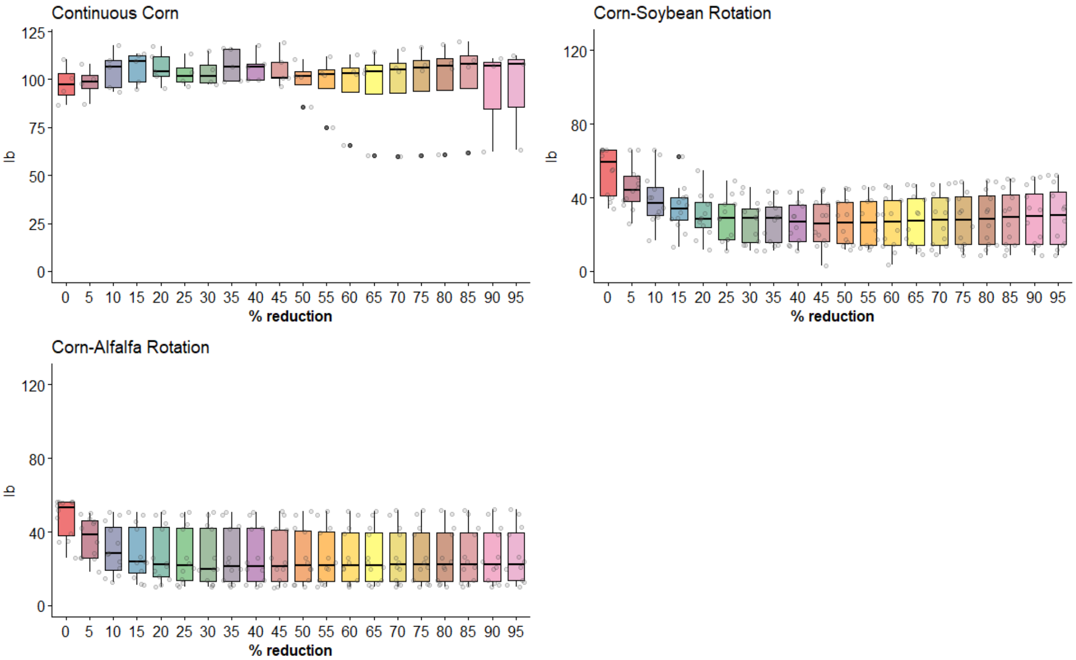


Figure 4. Status Quo Input Use and Externality Production by Year and Rotation
Notes: The status quo is defined as a zero percent reduction in nitrate leaching (i.e., $\theta = 0$). The positive mathematical programming calibration ensures that the status quo replicates the reference conditions; in our case, the average land use, fertilizer use, and production levels for the period 2003-2014.

(a) Nitrogen Application Adjustments (Intensive Margin)



(b) Land Allocation Adjustments (Extensive Margin)

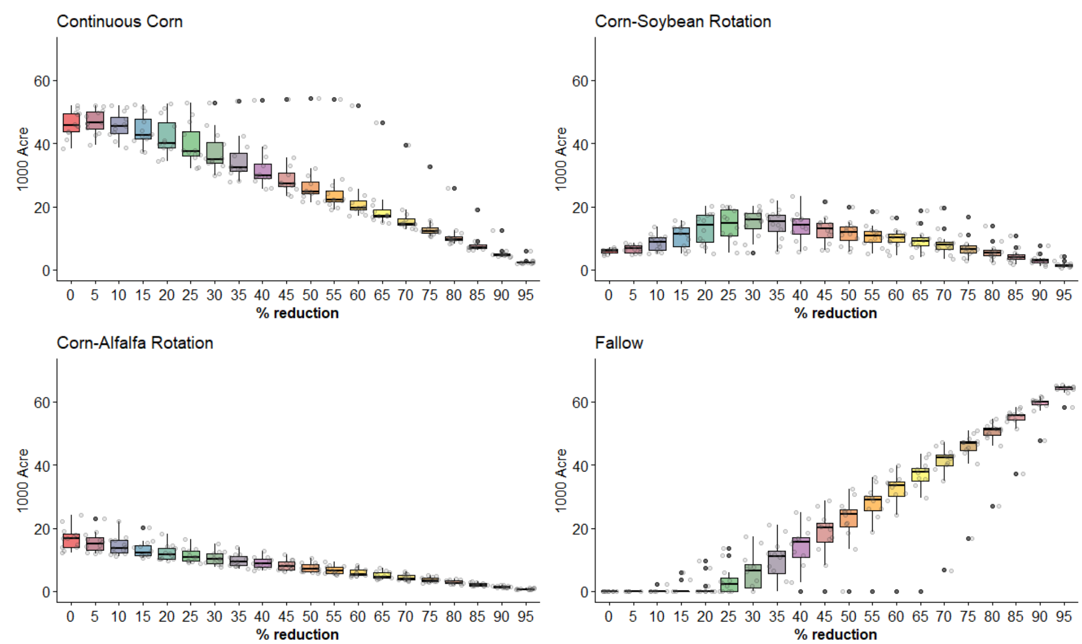
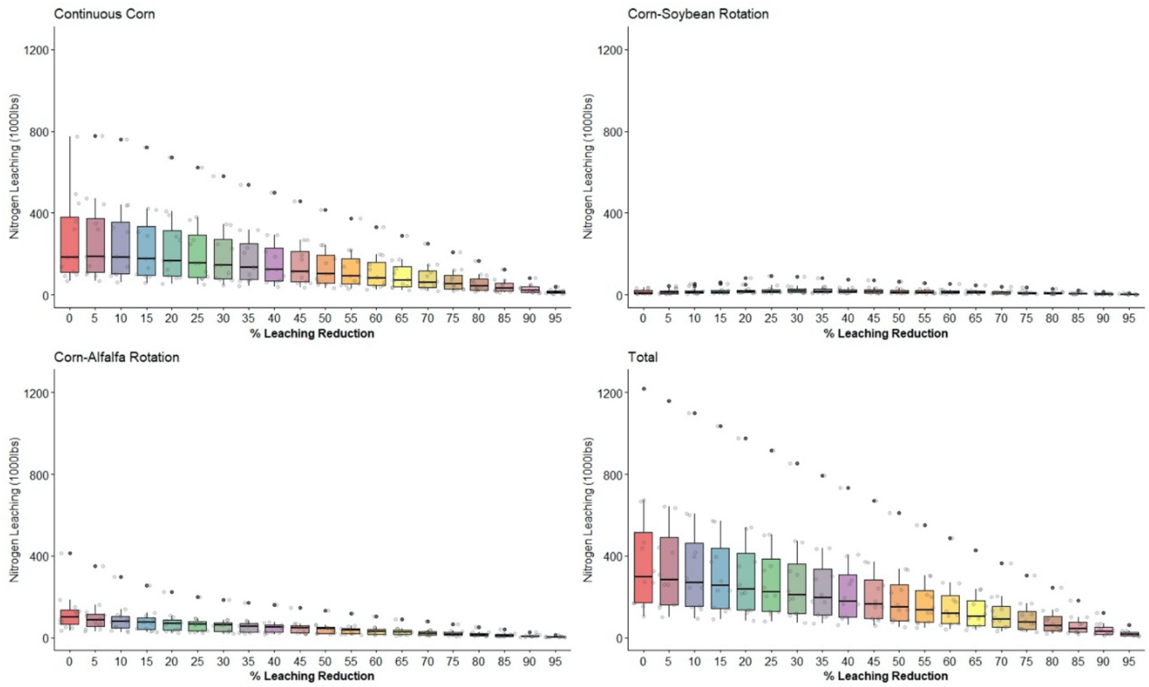


Figure 5. Behavioral Adjustments by Leaching-Reduction Scenarios

Notes: plot (a) displays per acre nitrogen application rate changes for three crop rotations modeled in the study area; plot (b) displays land use changes (in 1000 acres) in the study area. Total land area is 68884 acres and will not change across years. The box plot for each nutrient leaching constraint represents the distribution of simulation results across years (2003-2014). The center line in the box captures the median. The height of the box is defined by the first and third quartiles. Whiskers represent 1.5 times the interquartile range, defined as the height of the box.

(a) Nitrate Leaching Reductions



(b) Nitrous Oxide Emission Reductions

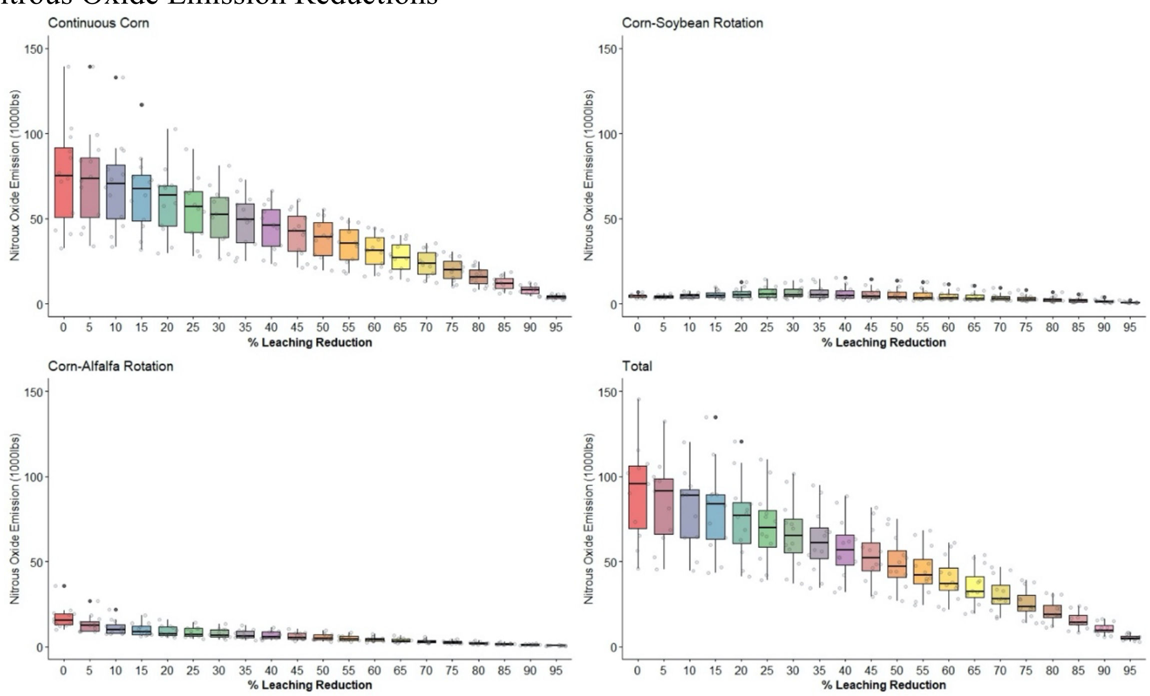


Figure 6. Pollution Levels by Leaching-reduction Scenarios

Notes: The box plot for each nutrient leaching constraint represents the distribution of simulation results across years (2003-2014). The center line in the box captures the median across years. The height of the box is defined by the first and third quartiles. Whiskers represent 1.5 times the interquartile range, defined as the height of the box. Individual points lie outside this range.

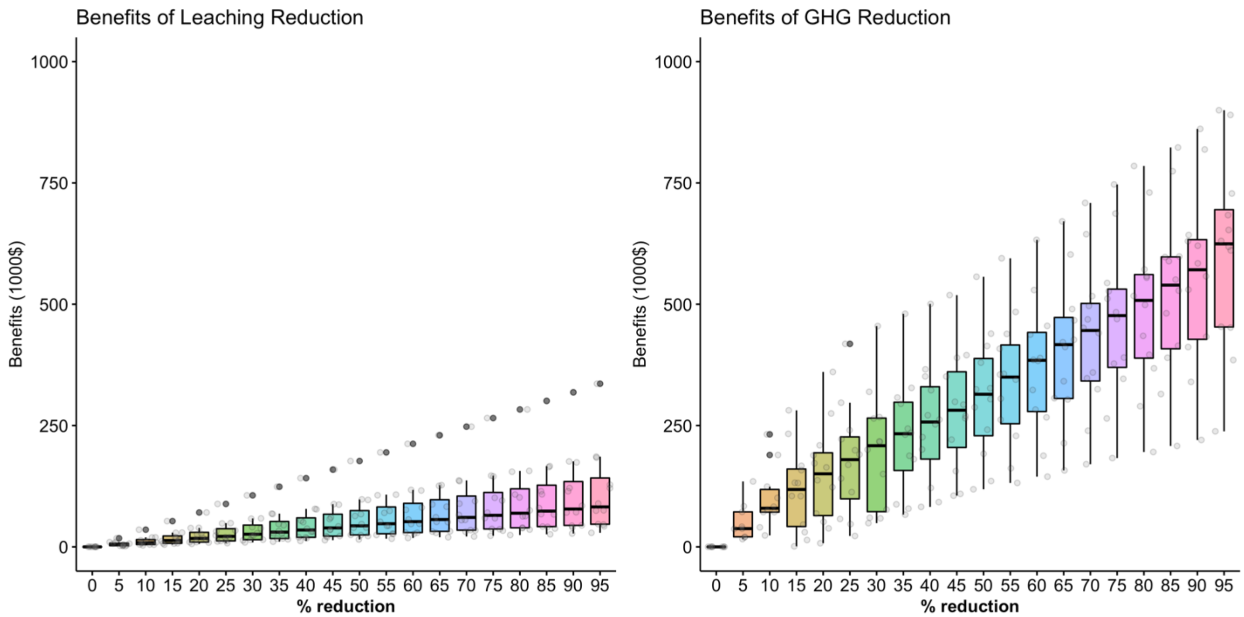


Figure 7. Monetary Benefits of Leaching and Emission Reductions by Leaching-reduction Scenarios

Notes: The box plot for each nutrient leaching constraint represents the distribution of simulation results across years (2003-2014). The center line in the box captures the median across years. The height of the box is defined by the first and third quartiles. Whiskers represent 1.5 times the interquartile range, defined as the height of the box. Individual points lie outside this range.

Table 1. Input Costs and PMP Calibrated Adjustment Terms ($/ac)

Rotation and commodity	Per-unit land cost (c_{Lij}) + initial shadow value ($\bar{\lambda}$)	Calibrated adjustment for land (λ_{Lij})	Per-unit nitrogen fertilizer cost (c_{Nij})	Calibrated adjustment for fertilizer (λ_{Nij})	Adjusted Per-unit nitrogen fertilizer cost
Continuous corn					
Corn	416.04	–271.03	0.70	–0.01	0.69
Two-year corn-soybean					
Corn	411.11	–262.54	0.84	–0.59	0.26
Soybean	306.94	–157.44	2.88	–2.88	0
Six-year alfalfa-corn					
Alfalfa (year 1)	307.62	–129.33	6.40	–6.40	0
Alfalfa (year 2)	253.58	–22.49	5.47	–5.47	0
Alfalfa (year 3)	253.58	–26.14	5.47	–5.47	0
Corn (year 1)	415.30	–256.40	2.81	–2.31	0.5
Corn (year 2)	415.33	–246.79	0.86	–0.75	0.11
Corn (year 3)	416.04	–242.72	0.70	–0.65	0.05

Table 2. Leaching and Emissions Reduction Benefits and Benefit-Cost Ratios, by Leaching-Reduction Scenario

Leaching constraint (% reduction)	Reduction ($x10^3$ lbs.)		Benefits ($x10^3$ USD)		Cost ($x10^3$ USD)	Benefit-cost ratio	
	Leaching	Emissions	Leaching	Emissions		w/out co-benefits	w/co-benefits
5	20.5	5.5	5.96	37.31	-1469.44	-0.004	-0.03
10	41.1	12.1	11.91	82.08	-1301.51	-0.009	-0.07
15	61.6	17.2	17.87	116.97	-1010.01	-0.02	-0.13
20	82.2	22.0	23.83	149.62	-614.09	-0.04	-0.28
25	102.7	25.9	29.78	176.40	-111.36	-0.27	-1.85
30	123.2	28.6	35.74	194.60	482.81	0.07	0.48
35	143.8	33.4	41.69	226.79	1144.59	0.04	0.23
40	164.3	37.4	47.65	254.08	1865.75	0.03	0.16
45	184.9	41.3	53.61	281.10	2627.53	0.02	0.13
50	205.4	45.6	59.56	310.04	3501.64	0.02	0.11
55	225.9	49.9	65.52	339.31	4446.86	0.01	0.09
60	246.5	54.1	71.48	368.20	5510.41	0.01	0.08
65	267.0	59.0	77.43	401.10	6724.27	0.01	0.07
70	287.5	63.3	83.39	430.70	8112.15	0.01	0.06
75	308.1	67.8	89.34	460.88	9691.58	0.009	0.06
80	328.6	72.3	95.30	491.55	11528.26	0.008	0.05
85	349.2	76.8	101.26	522.38	13739.50	0.007	0.05
90	369.7	81.5	107.21	554.18	16562.56	0.006	0.04
95	390.2	88.8	113.17	603.61	20646.21	0.005	0.03

Supplementary Appendix for "Quantifying Co-Benefits of Water Quality Policies: An Integrated Assessment Model of Land and Nitrogen Management"

Table S1. Economic Literature on Crop Supply Elasticities

Citation	Journal	Region	Estimates	J–Score	Y–Score	R–Score	Sum Score
Corn							
Hendricks et al. (2014)	American Journal of Agricultural Economics	Iowa, Illinois, Indiana	0.40 (short run)	10	9.75	9	94.44%
Hendricks et al. (2014)	American Journal of Agricultural Economics	Iowa, Illinois, Indiana	0.29 (long run)	10	9.75	9	94.44%
Arnade & Kelch (2007)	American Journal of Agricultural Economics	Iowa	0.2	10	8	9	86.67%
Lin & Dismukes (2007)	Review of Agricultural Economics	North Central Region	0.17 (linear model)	9	8	9	85.56%
Lin & Dismukes (2007)	Review of Agricultural Economics	North Central Region	0.35 (acreage share model)	9	8	9	85.56%
Miao et al. (2015)	American Journal of Agricultural Economics	United States	0.68	10	10	5	77.78%
Chavas & Holt (1990)	American Journal of Agricultural Economics	North Central Region	0.15	10	3.75	9	67.78%
Howitt et al. (2012)	Environmental Modelling & Software	California	0.55	9	9.25	3	64.44%
Chembezi & Womacj (1992)	Journal of Agricultural and Applied Economics	United States	0.1	10	4.75	7	63.33%
Lee & Helmberger (1985)	American Journal of Agricultural Economics	United States	0.05	10	2.5	5	44.44%
Houck & Gallagher (1976)	American Journal of Agricultural Economics	United States	0.24 (lower bound)	10	0.25	5	34.44%
Houck & Gallagher (1976)	American Journal of Agricultural Economics	United States	0.76 (upper bound)	10	0.25	5	34.44%

Table S1 (continued). Economic Literature on Crop Supply Elasticities

Citation	Journal	Region	Estimates	J–Score	Y–Score	R–Score	Sum Score
Soybeans							
Hendricks et al. (2014)	American Journal of Agricultural Economics	Iowa, Illinois, Indiana	0.36 (short run)	10	9.75	9	94.44%
Hendricks et al. (2014)	American Journal of Agricultural Economics	Iowa, Illinois, Indiana	0.26 (long run)	10	9.75	9	94.44%
Arnade & Kelch (2007)	American Journal of Agricultural Economics	Iowa	0.314	10	8	9	86.67%
Lin & Dismukes (2007)	Review of Agricultural Economics	North Central Region	0.3	9	8	9	85.56%
Miao et al. (2015)	American Journal of Agricultural Economics	United States	0.63	10	10	5	77.78%
Miller & Plantinga (1999)	American Journal of Agricultural Economics	Iowa	0.95	10	6	9	77.78%
Orazem & Miranowski (1994)	American Journal of Agricultural Economics	Iowa	0.33	10	4.75	9	72.22%
Chavas & Holt (1990)	American Journal of Agricultural Economics	North Central Region	0.45	10	3.75	9	67.78%
Lee & Helmberger (1985)	American Journal of Agricultural Economics	Illinois, Iowa, Indiana, Ohio	0.25	10	2.5	9	62.22%
Choi & Helmberger (1993)	Journal of Agricultural and Resource Economics	United States	0.13	8	4.5	5	51.11%
Alfalfa							
Howitt et al. (2012)	Environmental Modeling and Software	California	0.44	9	9.25	3	64.44%
Knapp (1990)	Working Paper	California	0.61	3	3.75	3	33.33%

Table S2. Parameter Estimates for the Mitscherlich–Baule Yield Functions

	Yield function parameter				
Rotation and crop	α_i	β_{i0}	γ_i	β_{i1}	β_{i2}
Continuous corn					
Corn	–	126.765	0.422	0.014	0.005
Two–year corn–soybean					
Corn	–	38.972	3.426	0.026	–9.088
Soybean	55.093	–	–	–	–
Six–year corn–alfalfa					
Corn (year 1)	–	2.057	80.943	0.041	–37.943
Corn (year 2)	–	2.990	56.449	0.038	–56.456
Corn (year 3)	–	4.950	34.099	0.029	–78.982
Alfalfa (year 1)	4.470	–	–	–	–
Alfalfa (year 2)	5.828	–	–	–	–
Alfalfa (year 3)	5.734	–	–	–	–

Table S3. Parameter Estimates for the Nitrate Leaching Function, Continuous Corn Rotation

Year	Nitrate leaching function parameter		
	β_{i0}	β_{i1}	β_{i2}
2003	3.394	–0.028	0.0002
2004	4.966	–0.014	0.00006
2005	2.814	–0.023	0.0001
2006	6.987	–0.066	0.0003
2007	15.19	–0.157	0.0009
2008	11.67	–0.038	0.0002
2009	7.162	–0.063	0.0002
2010	20.86	–0.084	0.0004
2011	3.335	–0.010	0.00007
2012	2.634	–0.012	0.0002
2013	5.874	–0.017	0.0001
2014	2.623	–0.010	0.00004

Table S4. Parameter Estimates for the Nitrate Leaching Function, Two-year Corn-soybean Rotation

	Nitrate leaching function parameter		
Year	β_{i0}	β_{i1}	β_{i2}
2003	1.334	–0.0008	0.0001
2004	3.623	–0.011	0.00008
2005	0.811	0.007	0.000006
2006	2.366	–0.026	0.0003
2007	4.460	0.006	0.0009
2008	11.03	–0.016	0.0001
2009	2.254	–0.006	0.00009
2010	12.73	–0.115	0.00009
2011	2.189	0.012	0.000008
2012	1.240	0.048	0.00004
2013	2.284	–0.008	0.00006
2014	1.314	0.001	0.00002

Table S5. Parameter Estimates for the Nitrate Leaching Function, Six-year Corn-alfalfa Rotation

	Nitrate leaching function parameter		
Year	β_{i0}	β_{i1}	β_{i2}
Corn (year 1)			
2003	1.257	0.004	0.00004
2004	4.500	0.008	0.00001
2005	2.163	0.011	–0.00002
2006	8.902	0.053	0.00004
2007	19.40	0.048	0.0006
2008	6.011	0.007	0.0001
2009	3.770	0.013	0.00002
2010	60.12	0.285	0.0002
2011	2.542	0.008	–0.00001
2012	5.244	0.042	0.000009
2013	3.652	0.006	0.00001
2014	2.210	0.00004	0.000005
Corn (year 2)			
2003	5.56	0.049	–0.00005
2004	13.26	–0.006	0.0002
2005	3.74	0.021	–0.00001
2006	10.35	0.107	–0.00001
2007	20.06	0.155	0.0004
2008	31.83	–0.084	0.0005
2009	11.66	–0.051	0.0003
2010	40.80	–0.033	0.001
2011	15.03	0.166	–0.0004
2012	16.31	0.079	–0.0001
2013	11.14	0.090	–0.0001
2014	7.241	–0.003	0.00003
Corn (year 3)			
2003	5.065	0.0241	–0.00006
2004	20.16	0.0230	0.0002
2005	3.867	–0.007	0.00005
2006	7.522	0.016	0.00008
2007	9.027	0.063	0.0001
2008	28.53	–0.044	0.0003
2009	10.02	–0.083	0.0003
2010	30.88	–0.116	0.0008
2011	5.862	–0.0007	0.00007
2012	11.58	0.033	–0.0001
2013	16.92	0.052	–0.00007
2014	10.32	–0.005	0.00002

Table S6. Parameter Estimates for the Nitrous Oxide Emission Function, Continuous Corn Rotation

	Nitrous oxide emission function parameter		
Year	β_{i0}	β_{i1}	β_{i2}
2003	0.480	–0.00009	0.00004
2004	0.601	0.005	0.00004
2005	0.494	–0.00003	0.00003
2006	0.667	0.003	0.00003
2007	0.653	–0.001	0.00004
2008	0.453	0.005	0.00002
2009	0.585	0.0006	0.00003
2010	0.889	0.002	0.00005
2011	0.598	–0.002	0.00005
2012	0.306	0.002	0.00004
2013	0.537	0.006	0.00005
2014	0.610	–0.00001	0.00005

Table S7. Parameter Estimates for the Nitrous Oxide Emission Function, Two-year Corn-soybean Rotation

Year	Nitrous oxide emission function parameter		
	β_{i0}	β_{i1}	β_{i2}
2003	0.646	–0.0004	0.00008
2004	0.634	0.010	0.00004
2005	0.479	0.005	0.00006
2006	0.625	0.003	0.00005
2007	0.603	0.0006	0.00009
2008	0.412	0.007	0.00002
2009	0.510	0.004	0.00005
2010	0.838	0.008	0.00005
2011	0.467	0.003	0.00008
2012	0.323	0.011	0.00002
2013	0.422	0.010	0.00003
2014	0.669	0.003	0.00008

Table S8. Parameter Estimates for the Nitrous Oxide Emission Function, Six-year Corn-alfalfa Rotation

	Nitrous oxide emission function parameter		
Year	β_{i0}	β_{i1}	β_{i2}
Corn (year 1)			
2003	0.631	0.0002	0.00008
2004	1.586	0.01	0.00007
2005	0.866	0.01	0.00002
2006	1.229	0.01	0.00009
2007	1.191	0.002	0.0001
2008	1.338	0.010	0.00006
2009	0.847	0.009	0.00006
2010	5.093	0.052	0.000008
2011	0.882	0.016	0.00005
2012	0.816	0.016	0.000005
2013	1.082	0.009	0.00008
2014	1.091	0.003	0.00010
Corn (year 2)			
2003	1.117	0.007	0.00007
2004	1.266	0.006	0.00007
2005	0.836	0.002	0.00006
2006	1.653	0.005	0.0001
2007	1.145	0.002	0.0001
2008	0.726	0.005	0.00003
2009	0.822	–0.0005	0.00007
2010	1.920	0.002	0.0001
2011	1.022	0.006	0.00007
2012	1.244	0.016	0.000003
2013	1.521	0.009	0.00007
2014	1.047	–0.002	0.0001
Corn (year 3)			
2003	0.828	0.003	0.00007
2004	1.145	0.007	0.00006
2005	0.609	–0.0003	0.00005
2006	1.075	0.0003	0.00009
2007	0.970	0.0002	0.0001
2008	0.647	0.005	0.00003
2009	0.729	–0.0005	0.00005
2010	1.432	0.002	0.00009
2011	0.660	0.006	0.00006
2012	0.873	0.016	0.000002
2013	1.283	0.009	0.00006
2014	0.954	–0.002	0.00009

Table S9 Lower and Upper bounds of Benefit-Cost Ratios

Leaching constraint (% reduction)	Benefits, lower bound ($x10^3$ USD)		Benefit-cost ratio, lower bound		Benefits, upper bound ($x10^3$ USD)		Benefit-cost ratio, upper bound	
	Leaching	Emission	without co-benefits	with co-benefits	Leaching	Emission	without co-benefits	with co-benefits
5	4.52	37.31	-0.003	-0.03	7.39	37.31	-0.005	-0.03
10	9.04	82.08	-0.007	-0.07	14.79	82.08	-0.01	-0.07
15	13.56	116.97	-0.013	-0.13	22.18	116.97	-0.02	-0.14
20	18.07	149.62	-0.03	-0.27	29.58	149.62	-0.05	-0.29
25	22.59	176.40	-0.20	-1.79	36.97	176.40	-0.33	-1.92
30	27.11	194.60	0.06	0.46	44.36	194.60	0.09	0.49
35	31.63	226.79	0.03	0.23	51.76	226.79	0.05	0.24
40	36.15	254.08	0.02	0.16	59.15	254.08	0.03	0.17
45	40.67	281.10	0.02	0.12	66.55	281.10	0.03	0.13
50	45.19	310.04	0.01	0.10	73.94	310.04	0.02	0.11
55	49.70	339.31	0.01	0.09	81.33	339.31	0.02	0.09
60	54.22	368.20	0.01	0.08	88.73	368.20	0.02	0.08
65	58.74	401.10	0.009	0.07	96.12	401.10	0.01	0.07
70	63.26	430.70	0.008	0.06	103.52	430.70	0.01	0.07
75	67.79	460.88	0.007	0.05	110.91	460.88	0.01	0.06
80	72.30	491.55	0.006	0.05	118.31	491.55	0.01	0.05
85	76.82	522.38	0.006	0.04	125.70	522.38	0.009	0.05
90	81.33	554.18	0.005	0.04	133.09	554.18	0.008	0.04
95	85.85	603.61	0.004	0.03	140.49	603.61	0.007	0.04

Table S10 Precipitation Levels by Growing Seasons

Year	ppt (inches)
2003	2.97
2004	4.12
2005	2.23
2006	4.63
2007	4.63
2008	4.55
2009	3.80
2010	5.14
2011	2.95
2012	2.84
2013	4.57
2014	4.88

Notes: growing seasons is defined as April to October. We calculate average monthly precipitation levels during the growing seasons using data from PRISM (PRISM Group, 2014). The 30-years normal in our study is 4.14 inches. Thus, year 2010 is a wet year, year 2005 is a dry year, and year 2004 is a normal year.

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