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

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Highlights

- Significant co-benefits of greenhouse gas emission reductions are associated with current water policies
- A coupled economic agro-ecosystem model helps to quantify those co-benefits
- Co-benefits differ with interannual differences in weather and greenhouse gas emissions
- Incorporating associated co-benefits could potentially impact the benefit-cost ratio of current water policies

Abstract

Due to the nature of nitrogen cycling, water policies designed to address water quality concerns have the potential to provide benefits beyond water quality improvements. For example, policies targeting reductions in nitrogen fertilizer applications and to reduce leaching and improve water quality also reduce the emission of nitrous oxide, a potent greenhouse gas (GHG). Those effects that are favorable to human welfare but not count as the regulation's intent target are termed 'co-benefits'. We quantify the co-benefits of water policies due to reduced nitrous oxide emissions by coupling an economic optimization model with an agro-ecosystem model. Our results demonstrate that failing to account for co-benefits from nitrous oxide emissions abatement understates the benefits of water policy and drives a wedge between the regulated and socially optimal levels of nitrogen application. However, the magnitude of co-benefits is highly variable across years due to differences in weather conditions and also differs with the stringency of the water quality policy. We demonstrate that quantifying additional sources of environmental benefits could potentially impact the benefit-cost ratio of current water policies and even reverse the conclusions of a benefit-cost analysis.

1. Introduction

Nitrogen, applied in the form of commercial fertilizer, is a key input for agricultural production. The use of commercial fertilizers boosts crop yields, but application of nutrients beyond crop needs contributes to environmental degradation in myriad ways. For example, commercial fertilizer usage compromises water quality and contributes to climate change simultaneously (Woodward 2011). Excess nitrogen leaches through the soil and into surface waterways and groundwater resources in the form of nitrate (NO_3^-), which contributes to the eutrophication of surface water bodies, contamination of drinking water supplies, and induce adverse health impacts, among other adverse effects. At the same time, excess nitrogen is emitted in the form of nitrous oxide (N_2O), a greenhouse gas (GHG) with high global warming potential.

Due to the nature of nitrogen cycling and the joint production of pollutants, water policies designed to address water quality concerns have the potential to provide benefits beyond water quality improvements, such as reduced greenhouse gas emissions. Those effects that are favorable to human welfare but not count as the regulation's intent target are termed 'co-benefits' (Aldy et al. 2020). Quantification of co-benefits are are widely used in the assessment of climate change mitigation policies (Ürge-Vorsatz et al. 2014; Nemet et al. 2010; Thompson et al. 2014). In the literature, there are also several studies which considered the co-benefits from carbon sequestration (e.g., Plantinga and Wu 2003, Feng et al. 2007). However, there has been little study to date (we are aware of one study by Gasper et al. 2012) that has evaluated the magnitude of co-benefits in the context of policy for water quality.

In this paper, we highlight the importance of co-benefits in the evaluation of water quality policies, observing that co-benefits of water policy can be an important decision criterion in cost-benefit analysis. However, these co-benefits are often neglected, and are not quantified or monetarized in policy adoption. Not accounting for co-benefits from nitrous oxide emissions abatement understates the benefits of nitrogen reductions and drives a wedge between the regulated and socially optimal levels of nitrogen application. If these ancillary benefits are significant enough, then perhaps the development and implementation of current policy should be altered (Krupnick et al. 2000). Furthermore, the amount of co-benefits could serve as an incentive for environmental improvements, and could be critical to establishing efficient and effective environmental markets (Liu and Swallow, 2015). Thus, correctly accounting for these co-benefits may provide additional insight into the optimal design of, and benefits from, water quality regulations.

We provide an integrated modeling framework to quantify the impacts of co-benefits under water policies that regulate nitrate leaching from agricultural production while also considering the co-benefits from nitrous oxide emission reductions. Specifically, we integrate a constrained optimization model of producer land-use and fertilizer-application decisions with a process-based model of terrestrial nutrient dynamics. The resulting integrated assessment model captures an endogenous feedback loop between farmer decision making and crop yields, and allows us to track the simultaneous generation of nitrate leaching and nitrous oxide emissions due to fertilizer applications.

We apply our model to analyze the Lake Mendota catchment in Wisconsin, USA, an agriculture-dominated watershed with a long history of water-quality degradation. Current and historic agricultural land-management decisions in this catchment are the primary drivers of ongoing water quality concerns in the region. In this context, there is a clear need to understand how policy tools could be used to adjust water quality concerns and to assess the benefits and costs of different policy options. Thus, we impose a series of increasingly stringent water policies, which ranges from 5% reduction from status quo to 95% of reduction from status quo, to regulate nitrate leaching (NO_3^-) from agricultural production. We simulate land owners' behavioral adjustments to these policies, which include changes in the amount of land allocated to the production of different crops as well as fertilizer applications, and calculate the associated changes in nitrate leaching and emissions under each policy. We then calculate the monetary value of these environmental benefits and evaluate the benefit-cost ratio with or without the inclusion of co-benefits due to emissions reductions.

Our coupled model suggests that nitrate oxide emission reductions correspond proportionately with changes in nitrate leaching: a 10% reduction in nitrate leaching is associated with a 12% reduction in nitrate oxide emissions and a 30% reduction in nitrate leaching is associated with a 27% reduction in nitrate oxide emissions. We also find that the co-benefits from nitrous oxide emissions are highly variable across years because of interannual variation in weather and economic conditions. Variation in weather conditions (e.g., precipitation timing and quantity) affects the relationship between fertilizer applications and environmental outcomes, whereas variation in economic conditions (e.g., relative crop prices) affects the behavioral adjustments made by farmers to meet water quality standards. We also demonstrate the importance of accounting for co-benefits when designing environmental policy. We find that across years, accounting for the co-benefits would increase the benefit-cost ratio, and in some circumstances would even change the results of cost-benefit analysis.

Overall, this paper provides several contributions to the literature. First, we demonstrate the advantages of utilizing an integrated assessment model in support of benefit-cost analyses of water policies. By advancing the science and methods of valuation, our framework helps to provide estimates of certain benefits, which is hard to quantity or monetize in the previous literature. Second, we provide evidence of the importance of a thorough understanding of the co-benefits associated with water policies. Our results suggest that there are significant nitrous oxide emission reductions associated with water quality regulation, and that accounting for those reductions can alter the findings of cost-benefit analyses used to support the adoption (or not) of current water policies. Third, we highlight the importance of understanding the heterogeneity in co-benefits as weather and economic conditions vary. Optimal policy levels would differ when considered different behavioral adjustments, thus more analysis would need in the future to determine the efficacy and cost-effectiveness of the policy program.

2. Methods

2.1 Overview

We use Lake Mendota Watershed located in Madison, Wisconsin as an example to illustrate our integrated modeling framework (Figure 1). Lake Mendota is the largest and deepest lake in the Yahara chain of lakes, and the watershed is dominated by mostly agricultural land. From year 2003 to year 2014, the dominant crop rotations in the Mendota catchment are continuous corn (67.4%), corn-soybean (8.4%) and corn-corn-corn-alfalfa-alfalfa-alfalfa (24.2%). The modeled crops and fallow land represent 10.64% of total land use in catchment.[1] The total acreage

[1] If we just consider agricultural lands, our calibrated land allocation represents 23.51% of the total agricultural lands.

allocated to crop production varies across years, ranging from 8.6% to 11.4% of the total agricultural land base in the lake catchment.

We use command-and-control policy that regulates nitrate leaching from agricultural production as a representation of water policy tools, which mimics the practice of numeric nutrient criteria. We combine a constrained optimization model of producer land-use and fertilizer-application decisions calibrated using positive mathematical programming (hereinafter "PMP") with the Cycles agro-ecosystem model of terrestrial nutrient dynamics (hereinafter "Cycles") to predict land owners' behavioral adjustments in land use and fertilizer applications, as well as the associated environmental pollution in terms of nitrate leaching and nitrous oxide emissions. Our modeling framework captures yield response to exogenous factors (climate, soil type) and management decisions (fertilizer application, crop rotations), while also builds a functional relationship between land management decisions, nitrate leaching, and nitrous oxide emissions. Cycles provides simulated crop yield, nitrate leaching and nitrous oxide emissions by year, crop rotation, and nutrient applications and PMP allows us to reproduce observed production practices without adding artificial constraints and can easily be coupled with agro-ecosystem models to conduct agri-environmental policy analysis (Mérel and Howitt 2014).

As the illustration in the figure 2, the integrated process of Cycles and Economic Optimization models mainly reflected in the calibration process. In the calibration process, we utilize Cycles outputs to calibrate and estimate crop yield function with respect to N application. After that, we combine the yield function, agricultural survey and extension data, remote sensing data, and exogenous supply elasticities to calibrate the economic optimization model using PMP. Then we utilize Cycles outputs again to calibrate nitrate leaching and nitrate emission functions with respect to nitrogen application. The calibrates parameters would capture the underlying production process and the calibrated behavioral and environmental parameters would provide basises for the simulation process. In the simulation process, we first simulate land owner's decision-making in terms of land allocation acreages (x_{i1t}) and nitrogen application amount per acre (x_{i2t}) under different policy scenarios, then estimate associated environmental outcomes. After that, we calculate the monetary value of reductions in nitrogen leaching and nitrogen emissions, and then investigate the cost-benefit ratio with or without the inclusion of co-benefits.

2.2 Calibration Process

2.2.1 Cycles Agro-ecosystem Model (Cycles)

Cycles is a user-friendly, multi-crop, multi-year, process-based model with daily time step simulations of crop production and the water, carbon (C) and nitrogen (N) cycles. The model is an evolution of C-FARM (Kemanian and Stöckle, 2010) and is closely related to CropSyst (Stöckle et al., 2014). The hydrology is simulated with an adaptive sub-daily time step. The algorithms of heat and water transport were adapted from Campbell (1985). The reference evapotranspiration is calculated using the Penman-Monteith equation as formulated by Allen et al. (2006). Daily plant growth is based either on the radiation capture (light limited) and or on the realized transpiration (water limited), an approach that surrogates for a coupled transpiration and photosynthesis model (Kremer et al., 2008). In Cycles, the stomatal conductance is determined by temperature and the leaf water potential, with the latter depending on the balance of the transpirational demand, the soil water supply and plant hydraulic properties (Jara and Stöckle, 1990; Camargo and Kemanian, 2016). Crop development is calculated using thermal time, and grain yield is calculated using the biomass accrued and the harvest index (Kemanian et al., 2007). Soil organic N and N cycling is 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), soil description (layer thickness, clay, sand and organic matter content), cropping sequence, and management information.

The model can simulate perturbations of biogeochemical processes caused by agronomic practices such as tillage, irrigation, organic and inorganic nutrient applications, annual and perennial crops selection, grain and forage harvest, polycultures, relay cropping and grazing. Cycles allows unlimited crop species to be specified by the user. For these simulations we used Cycles 0.5.0-alpha.

The dominant crop rotations in the Mendota watershed are corn-soy, corn-corn and three years of corn followed by three years alfalfa. Thus, we simulated the corn response to N fertilization rates considering both the rotation type and the year in the rotation in which corn was grown. In addition, we set up the simulation in a full-entry form, which means that every phase of each rotation was present ever year. To obtain corn responses to fertilizer that always reflected the same prior land use depending on the rotation, all rotations were run to steady state (i.e. when the soil organic N oscillated around a mean with drifting upward or downward in the long run) using the following fertilization rates: 160 kg ha^{-1} of N in the case of corn-corn, 120 kg ha^{-1} of N in the case corn-soybean, and 0, 60 and 120 kg ha^{-1} of N in the case of 1, 2, or 3 years after alfalfa. The soil properties including soil nitrate and ammonia in corn planting day in year of the sequence and for the reference fertilization rate in each rotation, were stored in a file called re-initialization file. The file was then fed to the corresponding rotation at run time, so that at the beginning of the corn growing season, all fertilization rates started up with the same soil conditions regardless (which of course varied for each year and rotation)[2].

2.2.2 Constrained Economic Optimization Model (PMP)

We build a watershed level economic optimization model, which maximizes net farm returns under regional resource constraints at year *t* (*t* = 2003, 2004, …, 2014)[3]:

$$\max_{q_{it} \geq 0, x_{ilt} \geq 0} \sum_{i=1}^{I} \{p_{it} q_{it} - [(c_{i1} + \lambda_{i1}) x_{i1t} + (c_{i2} + \lambda_{i2}) x_{i2t}]\} \tag{1}$$

Subject to

$$\begin{cases} \sum_{i=1}^{9} x_{i1t} + x_{ft} \leq b_{1t} \\ q_{it} = \mu_i \left[\sum_{l=1}^{2} \beta_{il} x_{ilt}^{\rho_i}\right]^{\frac{\delta_i}{\rho_i}} \end{cases} \quad \forall i = 1, \dots, 9$$

where p_{it} is the price for rotation i (i=1 denotes continuous corn rotation, i=2 denotes corn following soybean rotation, i=3 denotes soybean following corn rotation, i=4 denotes corn first year following alfalfa rotation, i=5 denotes corn second year following alfalfa rotation, i=6 denotes corn third year following alfalfa rotation, i=7 denotes alfalfa first year following corn rotation, i=8 denotes alfalfa second year following corn rotation, i=9 denotes alfalfa third year following corn rotation) at time t , c_{il} is the cost of input l (l=1 denotes land, l=2 denotes nitrogen application), x_{ilt} is the choice variable, which represents the amount of input l used in the production of rotation i at time t, and x_{ft} represents the amount of land fallowed or idled.[4] The

[2] The model was tested using data from the long-term rotational experiment established in Arlington, WI, that included multiple fertilization rates. Depending on the preceding land use, the regression of the simulated versus observed had slopes of 0.98 to 1.14, intercepts of -0.18 to -1.77, and R2 of 0.62 to 0.72. The regression of simulated versus observed N in the grain had comparable slopes but slightly more degraded R2 of 0.44 to 0.60, which are still rather satisfactory for simulations with no model calibration.
[3] Following Heckelei and Wolff 2003; Mérel et al. 2011; Mérel et al. 2013; Garnache et al. 2017, we use general constant elasticity of substitution (CES) function form for the crop rotation-specific production functions.
[4] Similar with Goldstein et al. (2012) and Medellín-Azuara et al. (2012), we assume zero profits for fallow/idle land use.

parameter b_l represents the available agricultural land, calculated as the sum of all crop acreages plus fallow acreages in the reference allocation. q_{it} denotes the output level, which depends on the parameters (μ_i, β_{il}, δ_i, ρ_i) of the CES function. The parameter ρ_i is defined as $\rho_i = \frac{\sigma_i - 1}{\sigma_i}$, where σ_i is the elasticity of substitution. The remaining CES production function parameters, μ_i, β_{il}, δ_i, λ_{i1}, and λ_{i2} are calibrated to ensure that both the first-order conditions for optimality in problem (1) as well as the second-order calibration conditions developed by Mérel et al. (2011) are satisfied for observed production practices.

2.2.3 Calibration Information

The model is calibrated to observed land share and cropping patterns for a reference situation taken as the average of the years 2003 to 2004. Cropping Patterns are constructed from Cropland Data Layer from USDA.

We use the one-year lagged crop prices to represent producers' expectation of prices at the time planting decisions and early season fertilizer applications are made. Commodity prices are taken from USDA NASS survey for year 2002 to 2013. In the calibration, we use the average price over all years to represent the long-run average commodity prices. In the simulation, we take the one-year lag of commodity prices to reflect producers' short-run expectations over future prices. All commodity prices are adjusted to the price level of 2010.[5,6]

Per-unit inputs are calculated using enterprise budgets, published by the University of Wisconsin Extensions (University of Wisconsin, 2014).[7] Costs of land include all operating costs other than fertilizer, which are assumed to be used in fixed proportion to land. Costs of all

[5] Website: https://www.nass.usda.gov/surveys/index.php
[6] Information source of information rate: http://www.usinflationcalculator.com/
[7] Enterprise budgets for Wisconsin are only available for years 2014 and 2015.

fertilizer inputs are included where phosphorus (P) and potassium (K) are assumed to be in fixed proportion to nitrogen (N).

Supply elasticities are summarized based on published economic literature (Table 1). We weigh reported supply elasticities using three criteria: 1) rank of the journal that publishes the study; 2) recency of the article; and 3) geographical proximity of the study region to Wisconsin. Each article is evaluated using these criteria using a score of 1-10, and the weight is assigned to be the sum of the scores (readers are referred to Table 1 for included studies and their respective weight assignments). Using this method, we construct own-price elasticities for corn, soybean, and alfalfa. The 95% confidence interval of own price supply elasticities for corn, soybean and alfalfa are [0.017, 0.630], [0.067, 0.740], and [0.363, 0.633], respectively.

2.2.4 Integrated Assessment Model

Our integrated assessment model focuses on the linkage of the Cycles and PMP, from which the outputs of Cycles served as the input of PMP.

Cycles provide the long run (1980-2015) field agronomic information for the Lake Mendota catchment and provide us the basis for the calibration of yield. For crop rotations Λ (Λ= continuous corn, corn following soybean, corn first year following alfalfa, corn second year following alfalfa, corn third year following alfalfa), Cycles provide simulated yield response by year with a range of nitrogen application rates, starting from 0 kg/ha to a maximum of 200 kg/ha (0 to 214.16 lb/ac), increasing by 10 kg/ha. Thus, we assume Mitscherlich-Baule functional forms for those five rotations to allow for a plateau in the fertilizer-yield relationship and factor substitution in crop production (Frank et al. 1990). Considering the minimal impacts of nitrogen applications for other four rotations (soybean following corn, alfalfa first year following corn, alfalfa second year following corn, and alfalfa third year following corn), Cycles assume the yield for those rotations would not be affected by N application, but would differ across years due to various weather conditions. Thus, we describe the relationship between yield and nitrogen applications at the observed level of nitrogen fertilizer applications ($\bar{a}_{iN}$) as:

$$\begin{cases} y_{it} = \beta_{i0}\left(1 + \boldsymbol{\gamma_{it}T} - \exp\left(-(\beta_{i1}) * (\beta_{i2} + N)\right)\right) + \varepsilon_{it} & if\ i\ \in \Lambda \\ y_{it} = \alpha_{it} & if\ \ i \notin \Lambda \end{cases} \tag{2}$$

where y_{it} is the grain yield for rotation *i* at year *t*, **T** denotes year-specific dummy variables; *N* denotes the nitrogen application rate, and $\beta_{i0}, \boldsymbol{\gamma_i}, \beta_{i1}, \beta_{i2}$ are estimated parameters. Estimated β_{i0} represents the average plateau growth in the long run, and $\boldsymbol{\gamma}$ represents the year specific plateau premium; estimated β_{i1} captures the average influence of nitrogen application in the long run, and estimated β_2 represents the natural factor endowments. The elasticity of yield with respect to nitrogen application at the reference yield ($\bar{y}_i$) can then be computed as:

$$\begin{cases} \bar{y}_{iNt} = \frac{\beta_{i0}(\beta_{i1})\exp\left(-(\beta_{i1})(\beta_{i2}+N)\right)\bar{a}_{iN}}{\bar{y}_i} & if\ i\ \in \Lambda \\ 0 & if\ \ i \notin \Lambda \end{cases} \tag{3}$$

A comparison between Cycles outputs and the fitted Mitscherlich-Baule production functions is depicted in figure 3. The estimated yield curves fit the original data well, with an R^2 larger than 0.98 for all crop rotations in our model.

After specify the elasticity of yield, we then calibrate the set of economic parameters (μ_i, β_{il} , δ_i, ρ_i, λ_{i1}, λ_{i2}) in equation (1). We calibrate the parameters against observed supply elasticities and followed the calibration procedure of Merel et al. (2011) and Merel et al. (2013). We first calibrate the elasticity of substitution σ_i by draw the elasticity of substitution parameter from a lognormal distribution with mean 1.15 and variance 0.5.[8] In the second step, we calibrate

[8] Hertel et al. (1996) empirically estimated the elasticity substitution between land and nitrogen for corn production in Indiana to be around 1.15, thus we adopt this information in our calibration.

the modeled supply elasticities (δ_i) against the exogenous supply elasticities. We ensure that the two calibration criteria hold per Merel et al. (2011), and solve for the parameters in the CES production function that ensure the model captures supply response that reflects exogenous supply elasticities estimated in the economic literature. In the third step, we use the yield elasticity in equation (3) to calibrate the production function parameters μ_i and β_{il}. Finally, we solve for the behavioral parameters λ_{i1} and λ_{i2} to reflect the crop-specific shadow costs of land and nitrogen fertilizer. These shadow cost parameters are the input cost adjustment terms that rationalize observed economic behavior, given prices and the calibrated CES production function. They are chosen such that the first-order conditions for optimality hold for model (1):

$$\begin{cases} p_i \bar{q}_i (\delta_i - \bar{y}_{iN}) = (c_{i1} + \lambda_{i1} + \bar{\lambda}) \bar{x}_{i1} \\ p_i \bar{q}_i \bar{y}_{iN} = (c_{i2} + \lambda_{i2}) \bar{x}_{i2} \end{cases} \tag{4}$$

where $\bar{\lambda}$ is the reference shadow value of land (Howitt 1995; Heckelei and Wolff 2003). These conditions hold as long as the conditions for the calibration against the exogenous supply elasticities hold (Merel et al. 2011).

We calibrate $\bar{\lambda}$ following Garnache et al. (2017). Their method chooses the reference shadow value that minimizes the sum of squared deviations between the modeled activities and input-level expenditures and their observed values in the reference allocation.

We utilize Cycles outputs to calibrate pollution production functions with respect to N application. Specifically, we consider two outcomes: nitrate (NO_3^-) leaching into groundwater and freshwater bodies, and nitrous oxide (N_2O) emissions into the atmosphere. We estimate leaching and emissions functions based on Cycles simulation outputs for each crop in each year from 2003 to 2014 and with nitrogen fertilizer applications ranging from 0 to 200 kg/ha (0 to 214.1643 lb/ac). Simulated leaching and emission data are fitted with a quadratic function with year-specific constant terms and slopes:

$$\begin{cases} e_{nit} = \beta_{i0t} + \beta_{i1t}N + \beta_{i2t}N^2 + \varepsilon_{it} & if\ i\ \in \Lambda \\ e_{nit} = 0 & if\ \ i \notin \Lambda \end{cases} \tag{5}$$

where *n* denotes nitrate form *n* ($n = NO_3^-, N_2O$). Detailed coefficient estimates are reported in Appendix S2-S11. The quadratic functional form fits the simulation data well, with an average R^2 of 0.98 across crop rotations.

2.3 Simulation Process and the Quantification of Co-benefits

In our analysis, we impose a command-and-control policy to regulate nitrate leaching (NO_3^-) from agricultural production. To reflect the impacts of policy stringency, we assume a leaching reduction constraint starting from 5% of reduction from status quo to 95% of reduction from status quo, and simulate the results for every 5% increase in reduction level. We assume the regulator has complete information about the amount of nitrate leaching associated with production practices, and is capable of implementing 5% to 95% reduction caps for all agricultural producers in the watershed.

After imposing different policy constraints into the model, we use calibrated parameter to simulate land owner's decision-making in terms of land allocation acreages (x_{i1t}) and nitrogen application amount per acre (x_{i2t}), and then calculate the amount of environmental outputs using:

$$E_{nt} = \sum_{i=1}^{9} e_{nit}\,(x_{i2t})x_{i1t} \tag{6}$$

Utilizing the simulation outputs of our Integrated Assessment Model, we compute three indicators to quantify the impacts of co-benefits: the absolute amount of nitrous oxide emissions, monetary value of nitrous oxide emissions and the change of benefit-cost ratio.

We first compute the absolute amount of nitrous oxide emissions using the following formula:

$$\Delta E_{N_2Ost} = E_{N_2Ost} - E_{N_2O0t} \tag{7}$$

Where ΔE_{N_2Ost} denotes the emission level change at policy scenario s and year t, E_{N_2Ost} denotes the emission level at scenario s and year t, E_{N_2O0t} denotes the baseline emission level at year t.

We compute the monetary value of the reduction in different N forms to quantify the monetary value of nitrous oxide emissions and to facilitate the calculation of benefit-cost ratio. The computation of the monetary value is based on the social cost of nitrogen, which reflect the present value of monetary damages caused by an uniary increase in N (Keeler et al., 2016). We adopt the monetary value documented in Keeler et al. (2016) and use a back-of-the-envelope calculation to calculate the total social costs of different N forms. According to Keeler et al. (2016), for nitrate leaching (NO_3^-), the average social costs of N from fertilizer application is \$0.01 per Kg N (\$); for nitrate emission (N_2O), the average number is \$0.22 per Kg N (\$) and the range varies from \$0.22 to \$0.22. The calculation is proceeded with the following formula:

$$B_{nst} = -SC_n * \Delta N_{st} \tag{8}$$

where B_{nst} represents the benefits of the reduction in nitrate form *n* ($n = NO_3^-, N_2O$) at policy stringency level *s* of year *t*, SC_n represents the social costs of per kg N from fertilizer application in nitrate form *n*, and N_{st} represents the reduction of total Nitrogen application, which is the product of per acre nitrogen application level under different crop rotations and land acreages of different crop rotations.

We also calculate the benefit-cost ratio with or without considering the amount of co-benefits to reflect the potential impacts on benefit-cost analysis. The cost is derived from the abatement costs, i.e., the forgone farming profits under leaching policies. We proceed the calculation of benefit-cost ratio using the following formula:

$$\begin{cases} \frac{B}{C}_{sto} = \frac{B_{NO_3^- st}}{Profit_{st} - Profit_{0t}} \\ \frac{B}{C}_{stc} = \frac{B_{NO_3^- st} + B_{N_2Ost}}{Profit_{st} - Profit_{0t}} \end{cases} \tag{9}$$

where $\frac{B}{C}_{sto}$ reflects the benefit-cost ratio without adding the co-benefits, $\frac{B}{C}_{stc}$ reflects the benefit-cost ratio with the co-benefits.

3. Results

3.1 Calibration Results

Calibrating the behavioral parameters λ_{i1} and λ_{i2} in equation (1) is essential to understand land owner's underlying behavioral, and λ_{i1} and λ_{i2} reflect the crop rotation specific shadow costs of land and fertilizer, respectively. In other words, λ_{i1} and λ_{i2} represents the needed unobserved adjustments to rationalize observed economic behavior, giving the economic information at hand. We report the calibrated parameters in table 2.

For all crop rotations, we have negative values for both λ_{i1} and λ_{i2}, which can be interpreted as hidden benefits from land use in agriculture and nitrogen fertilizer applications. Put differently, we are over-estimating the true cost of land and nitrogen application for these crop rotations. This is reasonable, given that we only have extension data for the year of 2014, and we use this data to present the average information across year 2003 to 2014. Although we have corrected for inflation, there is high possibility that our estimates are still higher than that on the ground for years that we do not observe economic data.

Among all the rotations, continuous corn rotation displays the largest hidden benefits of land, and followed by corn following soybean, corn first year following alfalfa, corn second year following alfalfa, and corn third year following alfalfa. The large number here indicates the unobserved benefits for corn. Alfalfa first year following corn displays the largest hidden benefits from applying nitrogen, followed by alfalfa second year following corn, alfalfa third year following corn, and soybean following corn. For those four crops, the shadow benefits would offset the market price of nitrogen. Figures 3(c), 3(g), 3(h) and 3(i) provides an explanation for this calibration, as extra nitrogen application does not create extra yield for these four crops. We also find that the shadow benefits of corn following soybean, corn first year following alfalfa, corn second year following alfalfa, corn third year following alfalfa offset a large proportion of the nitrogen costs, this finding also in accordance with the yield calibration in figures 3(b), 3(d), 3(e) and 3(f), as the observation point lies in the flatter portion of the yield response curve. The calibrated parameters suggest that land owners could reduce nitrogen in corn-soybean and corn-alfalfa rotations without losing much yield.

3.2 Status Quo Outputs

Using our calibrated parameters and fitted leaching and emission functions, we simulate yearly land use and fertilizer application decisions at a regional level, and compute associated yearly nitrate leaching and emission levels (Figure 4). Like observed land-use patterns (Figure 1), our simulation of status quo outputs suggests that the largest amount of acreage is allocated to the continuous corn rotation, followed by corn-alfalfa rotation and corn-soybean rotations. Per acre application of N has the similar pattern with land-use, in which continuous corn rotation has the largest N applied. Due to the amount of planted acreage and nitrogen applications, the continuous corn rotation contributes the greatest to environmental pollution in all rotations, followed by the corn-alfalfa rotation and then by the corn-soybean rotation.

Considering the varying nitrogen application levels and weather conditions, nitrate leaching and nitrous oxide emission levels vary by year. Our simulated results suggest that peak leaching occurs in the year 2010, with a magnitude six times larger than the level in the year 2003, the lowest year for nitrate leaching. The variance in emissions between years is relatively small compared to the variance in leaching, with peak emission occurring in the year 2013.

3.3 Results of Policy Experiments

In this section, we present results from our integrated assessment model that simulates the economic and environmental impacts of a command-and-control policy, which targets a reduction in nitrate leaching to the lake. To fulfill increasingly stringent leaching caps, land owners would adjust both their land allocation and the use of nitrogen fertilizer. Figure 5 displays the two behavioral adjustments for different crop rotations. Considering the underlying differences in years, we use the box plot to display the distribution of the data.

At the extensive margin, we see economically significant adjustments in land allocation under policy caps (Figure 5(a)). The acreage reallocation patterns seem quite consistent across crop rotations, except for corn-soybean rotation. The acreage of continuous corn and corn-alfalfa rotation decrease, while the acreage of fallow increase. For the corn-soybean rotation, acreages display an inverted-U shape response to more stringent leaching caps: acreage increases when the leaching caps are smaller than 30% and decrease thereafter. When leaching reduction reach 10%, we start to observe fallow land for several years, when leaching reduction reach 25%, we observe fallow land for majority of the years. When leaching policy become more stringent, the land acreage of fallow would expand accordingly.

At the 30% reduction in leaching, the acreage of continuous corn and corn-alfalfa are predicted to drop by 27.3% and 23%, when compared with the reference allocation. At the same time, 11% of the total land is predicted to be fallow land. For the corn-soybean rotation, acreages display an inverted-U shape response to more stringent leaching caps: acreage increases when the leaching caps are smaller than 30% and decrease thereafter. These extensive margin adjustments line up with the underlying agronomic relationships between nitrogen application and crop yield. Compared to the other rotations, continuous corn is the most sensitive rotation in terms of reacting to nitrogen application. Thus, it sees the greatest reduction in land allocation when the leaching cap becomes more stringent. Land areas removed from continuous corn are either fallowed or transitioned into a corn-soybean rotation.

There are significant increases in land fallowing under increasingly stringent leaching caps. Producers will fallow up to 60% of the land base when facing the most stringent policy cap (a 95% reduction in leaching).

Correspondingly, when tightening leaching caps, land owners would reduce the acreage allocated to the continuous corn and corn-alfalfa rotations. For the corn-soybean rotation, acreages display an inverted-U shape response to more stringent leaching caps: acreage increases when the leaching caps are smaller than 30% and decrease thereafter. These extensive margin adjustments line up with the underlying agronomic relationships between nitrogen application and crop yield. Compared to the other rotations, continuous corn is the most sensitive rotation in terms of reacting to nitrogen application. Thus, it sees the greatest reduction in land allocation when the leaching cap becomes more stringent. Land areas removed from continuous corn are either fallowed or transitioned into a corn-soybean rotation.

At the intensive margin, producer adjustments to leaching caps vary significantly by rotation. Figure 5(b) shows adjustments in fertilizer application intensity at different policy cap levels. Nitrogen application rates for the continuous corn rotation generally remain the same across different leaching caps. In contrast, both corn-soybean and corn-alfalfa rotations see significant reductions in nitrogen intensity with an increasingly stringent policy cap. This is also in line with the underlying agronomic model, which suggests that corn-alfalfa and corn-soybean rotations are over-fertilized at the baseline level.

Due to differences in baseline leaching levels, under the same reduction percentage cap, the absolute reduction amounts differ across years, and thus the behavioral adjustments also differ slightly across years. In general, the reduction in leaching under leaching cap policies is primarily driven by extensive margin adjustments in the land allocation, and less so by intensive margin adjustments in fertilizer application intensity.

As expected, leaching cap policies decrease nitrate leaching levels, as depicted in figure 7. Reductions in leaching are attributable primarily to a decrease in land allocated to the continuous corn rotation (see figure 6(a)), though a reduction in land allocated to the corn-alfalfa rotation also provides environmental benefits. Nitrate leaching from the corn-soybean rotation increases first with the cap, as land is reallocated from the continuous corn rotation into corn-soybean, then decrease after the cap becomes more stringent, when it is necessary to fallow land previously used in all three crop rotations.

3.4 Quantification of Co-benefits

Reductions in nitrous oxide emissions are positively correlated with reductions in nitrate leaching. This follows from the same behavioral adjustments, primarily changes in the land allocated to the continuous corn rotation. Considering the difference in behavior adjustments and the impacts of weather conditions, yearly variation exists for emission levels as well. In general, the largest reduction in emission happens in the year 2013, which is the year with the largest status quo emission levels. Overall, reductions in nitrous oxide emission are mostly in line with reductions in nitrate leaching percentagewise. For instance, when leaching falls by 10%, emissions decline by 11.2%; when leaching falls by 90%, emissions decline by 85%.

We calculate the monetary value of the associated nitrous oxide emission reductions (Table 3). The monetary value of nitrous oxide emission reductions come from the change in total nitrogen applications, which is a product of land reallocation and per acre nitrogen application change. As expected, the benefits of nitrous oxide emission reduction would increase as the increase of policy stringency. At a 30% leaching reduction level, the associated nitrous oxide emission reductions would bring more than $501,000 in monetary benefits to the society.

We also compare the economic benefits and costs with and without the consideration of the co-benefits. Interestingly, we find that when policy constraints are set at 25% or less, the policy actually results in a Pareto improvement, such that both the land owners and the environment are benefited. This win-win situation comes from correcting over-fertilization, and indicates that land owners could possibly reach mild leaching targets without losing any profits. [9] When we increase the policy constraints to above 30%, land owners will have to start fallowing land, and policy makers will face a trade-off between environmental benefits and forgone farm profits. We find a small benefit-cost ratio for water quality policies beyond 30% reduction in nitrogen, which echo's Keiser et al. (2019)'s finding. The tipping point for correction of over-

[9] In reality, due to the lack of information, overfertilization is very easy to happen. In the future, the optimal fertilization level could potentially be attained using precision production technologies, but in a typical production setting with uncertainty and risk aversion, we would expect producers to over-fertilize slightly.

fertilizer could be found at Table 4. Across all years, we find an average tipping level of 27% reduction, but due to the yearly differences, the reduction range could go from 16% to 40%.

When taking into account the co-benefits of nitrous oxide emissions, the benefit-cost ratio changes significantly. At a 30% leaching reduction level, without considering the co-benefits, we would have a benefit-cost ratio of 0.0473, after adding the co-benefits, the benefit-cost ratio would reach 1.0870. Considering the decision rule of cost-benefit analysis, this magnitude change would potentially reverse the benefit-cost analysis results.

4. Discussions and Policy Implications

Based on the simulation results, it appears that the water quality policies generate economically significant co-benefit from reducing nitrous oxide emissions, both in the volume of nitrous oxide reductions and in the monetary value of those reductions. Because these benefits accrue more broadly than the benefits of improved water quality, such that the social benefits from nitrous oxide emissions reductions accrue at a global scale, whereas the social benefits from improvements in lake water quality are more localized, we find that the co-benefits from reducing greenhouse gas emissions can be an order of magnitude greater than the social benefits from reductions in leaching. This finding also echo's the results of co-benefits in carbon sequestration: Glenk and Colombo (2011) use choice experiment method and find that incorporate co-benefits may change the outcome of cost-benefit tests in various soil carbon sequestration.

Our results also suggest that the magnitude of the co-benefits depends on the stringency of the policy instruments, which is due to the differences in behavioral adjustments. When water policy is less stringent, intensive margin change (i.e. change in per acre fertilization level) would dominate the results; when water policy become stringent, extensive margin change (i.e. change in land allocation) would dominate the results. As such, policy makers should take into consideration the differences in behavioral adjustments when design water quality policies, as that would determine the efficacy and cost-effectiveness of the program. At small reduction levels, policies to manage nitrogen-related pollution from agriculture can potentially focus on incentivizing or mandating reduced fertilizer applications. For larger targeted reductions in pollution, policies that alter land use rather than nitrogen inputs are likely to be more effective.

Given the fact that the implementation of land use change to reduce nitrate leaching will be costly to land owners, while the benefits largely accrue to the wider public, neglecting co-benefits for the design of water policy can lead inefficient outcomes. Our results suggest that the inclusion of co-benefits could play an important role in the design of best management practices (BMPs), such as the ranking of cost-effectiveness the adoption of BMPs. Policy makers could focus more on the BMP that could be used to achieve co-benefits and the amount of co-benefits could be used to re-assess the effectiveness of existing BMPs. For instance, if the co-benefits are substantial, the ranking of cost-effective BMP may need adjustments. Some BMPs that have been identified as cost-effective now may be viewed less favourably if impacts on nitrous oxide reductions are factored in. Further, when considering the adoption of BMPs, these co-benefits could generate additional financial incentives to land owners, i.e., land owners could sell the carbon offsets in the climate exchange market. The inclusion of co-benefits is extremely important adopting more expensive BMPs (e.g., forest buffers), those expensive BMPs are effective for stringent water polices, but have not seen high rates of adoption.

The quantification of co-benefits could also shed light on the design of water quality trading markets. Currently, the water quality trading markets are experience very few trade volumes (Ribaudo et al., 2010). One of the reasons is lack of incentives for participants. For BMPs with co-benefits, i.e., riparian buffer, could reduce nutrient pollution in runoff and also sequester GHG from the atmosphere, which generates participate in both water quality and GHG markets[10]. Land owners could use these practices to reduce nutrient pollution to local waterways and to serve as offsets in GHG markets. Policy makers could propose using stacking as a way to incentive adoption of BMPs, which could provide additional incentives for agents to participate in the market (Gasper et al. 2012). In addition, Liu and Swallow (2015) suggest that incorporate co-benefits may also improve the overall efficiency of a water quality trading market.

From the perspective of cost-benefit analysis, quantifying co-benefits is necessary for informing policy-makers about the potential effects of the regulatory action and our results suggest in the agricultural production side, the overall benefit-cost ratio is low for agricultural industry. Quantifying additional sources of environmental benefits can potentially tip the balance of cost-benefit analysis for water quality policies. Considering the co-benefits could provide an incentive for land owners to undertake costly changes in land use. For example, if land owners can trade the nitrous oxides emissions in regional or national GHG markets, the economic costs of abating environmental pollutions would decrease significantly. In addition, integrated the agricultural productions into opportunities for carbon market participation could also contribute to the reduction of greenhouse gas emissions.

5. Conclusion

Given the economic and environmental effects of nitrogen fertilizer use on crop production, water quality, and climate change, it is important to establish a modeling framework that links

[10] In the literature, this behavior is referred as “stacking”.

the physiochemical process of nitrogen cycling to land owners' decision making. In this paper, we integrate an economic mathematical programming model with an agro-ecosystem model to illustrate those linkages and to quantify the environmental and economic impacts of a leaching cap policy. By introducing the leaching cap policy into the framework, we simulate producers' behavioral adjustments in land use and nitrogen applications at the catchment scale and calculate the associated changes in nitrogen leaching and emissions. By introducing the leaching cap policy into the framework, we simulate producers' behavioral adjustments in land use and nitrogen applications at the catchment scale and calculate the associated changes in nitrogen leaching and emissions.

Empirically, we find that when nutrient reduction targets are small, reducing commercial fertilizer applications would be the preferred option. Otherwise, alternative crop rotations and land retirement will become more advantageous. When reduction targets are small, water quality policies could help land owners' correct the over-fertilization behavior and generate more profits at the intensive margin. Across all simulated years, a reduction level of 27% could serve as a tipping point for the correction of over-fertilizations.

Overall, our modeling approach provides a framework to link air and water pollutants in an agri-environmental system, and offers one possible direction for re-evaluating the environmental and economic benefits of current surface water polices.

Given the mixing nature of ecosystem services, the main target of environmental regulations would be a concern. To shed light on this question, we suggest in the future, more research is need to assess 1) the magnitude and spatial distribution of co-benefits derived from particular changes in agricultural practices, 2) policy design and implementation when multiple benefits and costs are presented.

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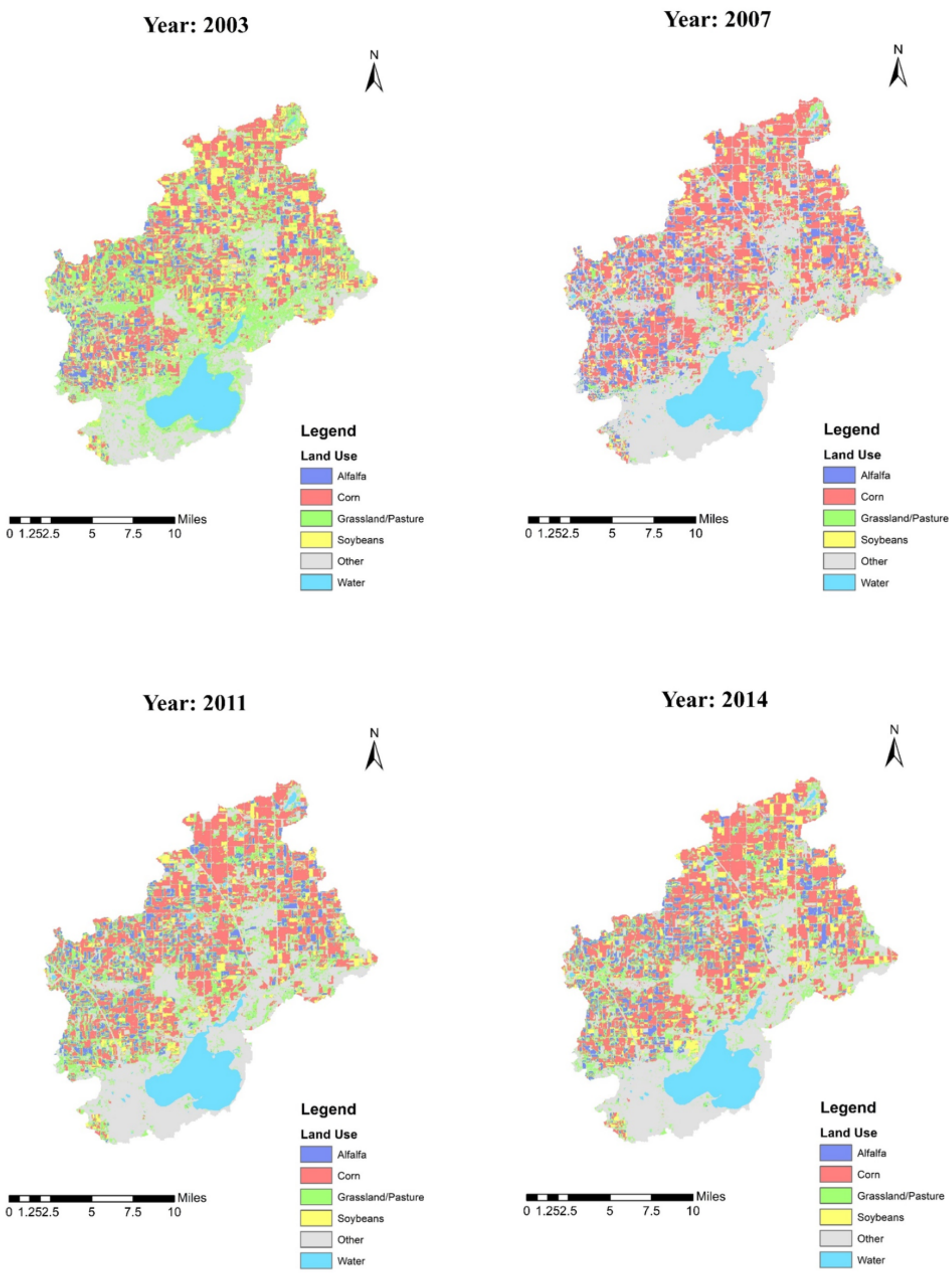
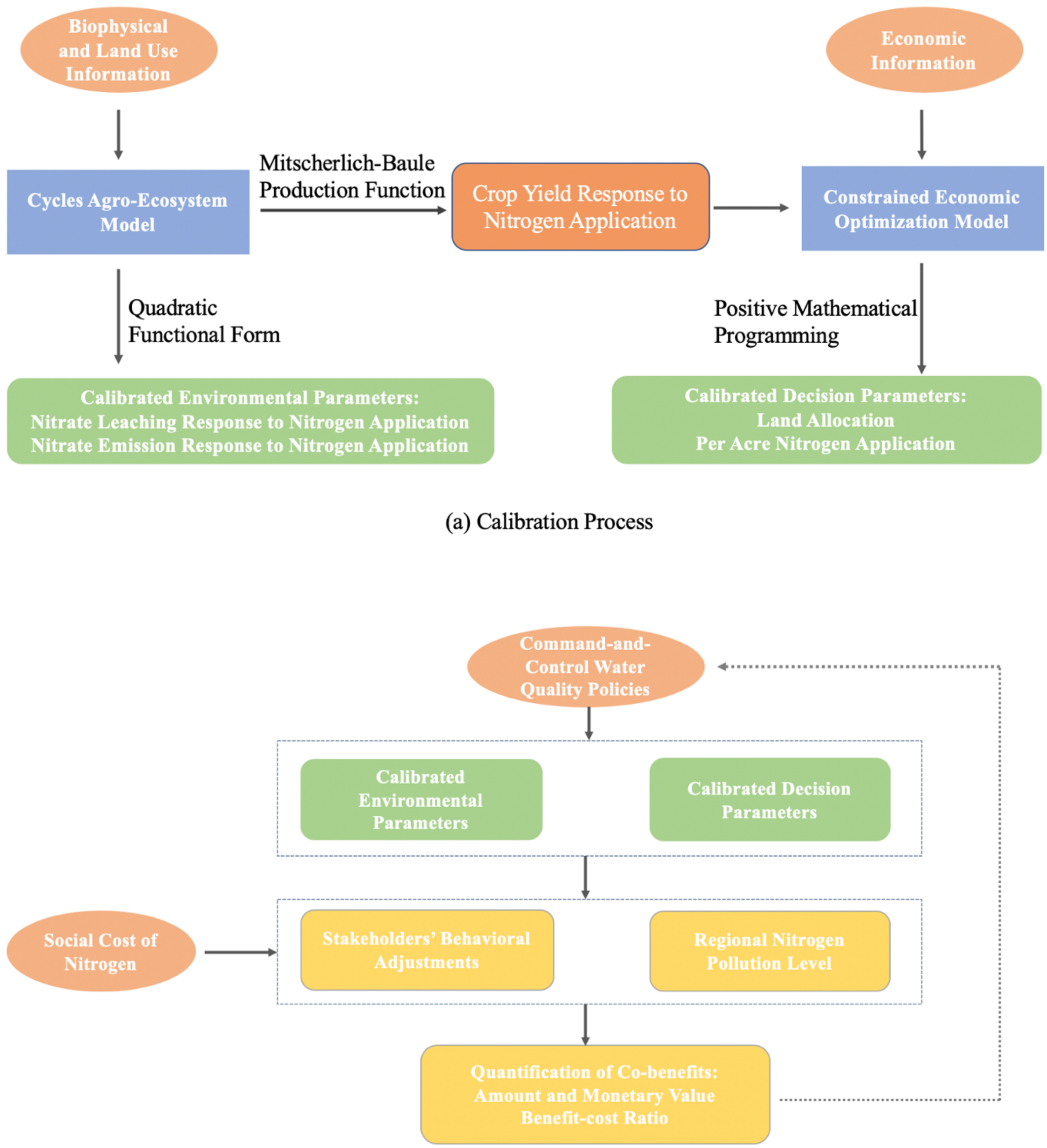


Figure 1. Land Use Change of Lake Mendota Watershed for Year 2003-2014.



(a) Calibration Process

(b) Simulation Process

Figure 2. Modeling framework linking water quality policy with land owners' behavioral adjustments, environmental pollution and cost-benefit ratios.

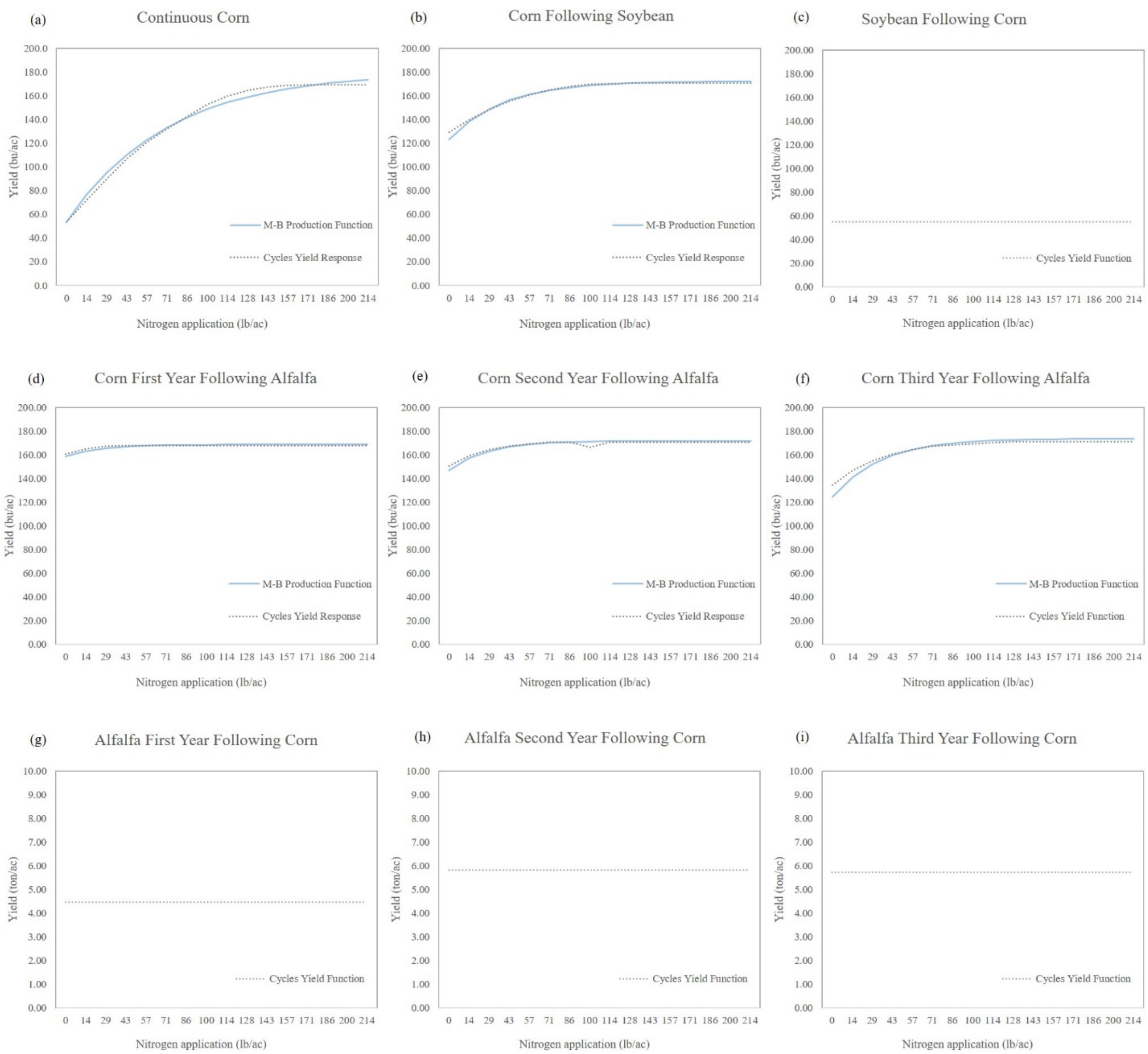


Figure 3. Per Acre Yield Response to Nitrogen Application.

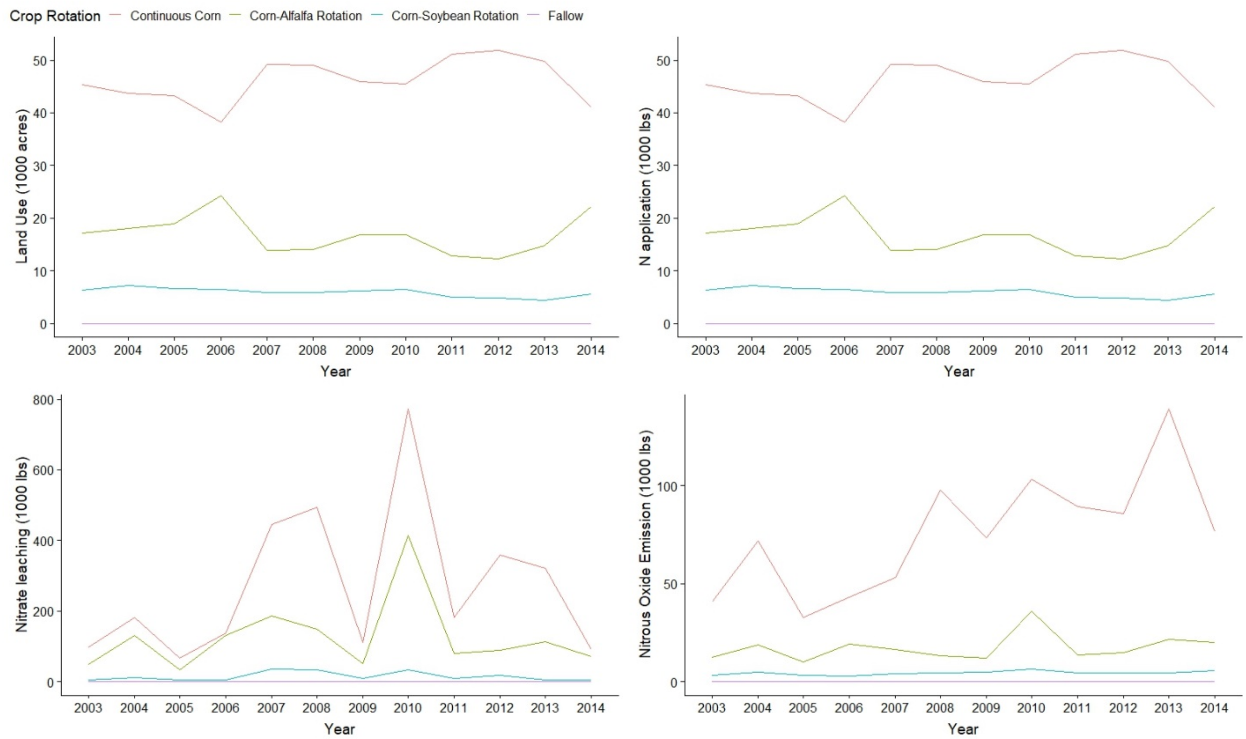
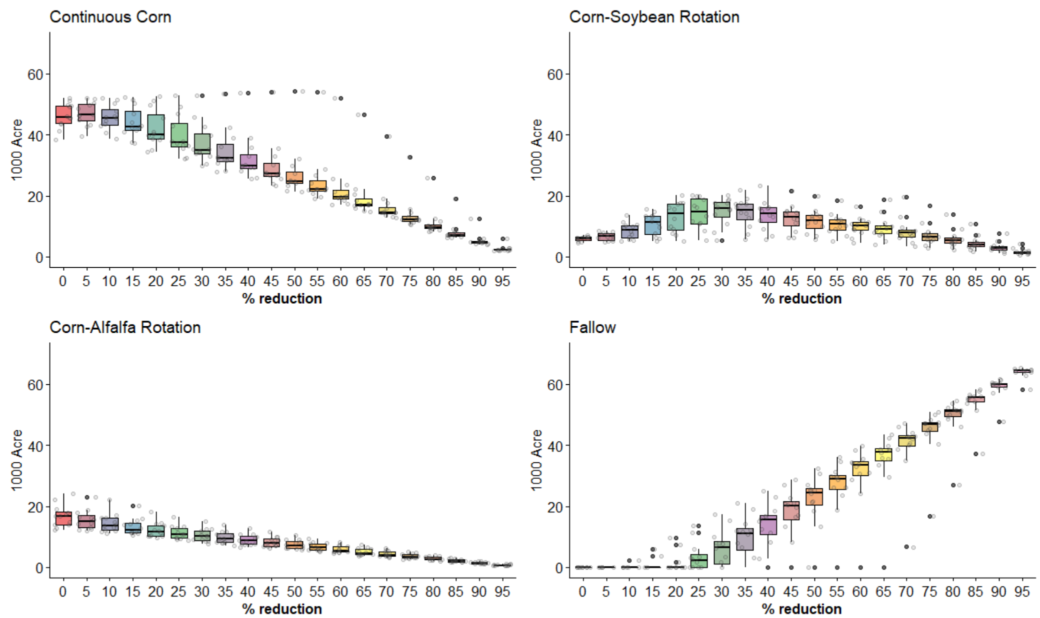


Figure 4. Status Quo Outputs of Land Use, Nitrogen Application, Nitrate Leaching and Nitrous Oxide Emissions.

(a) Land Allocation



(b) Nitrogen Application

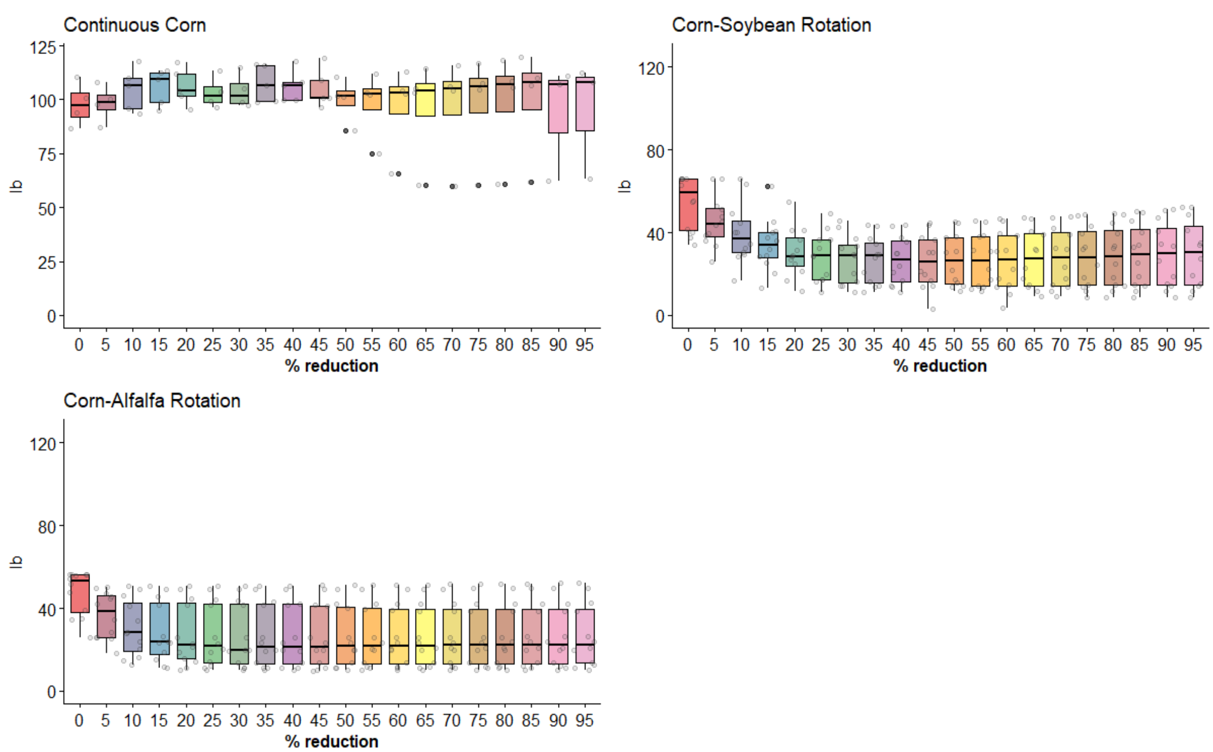
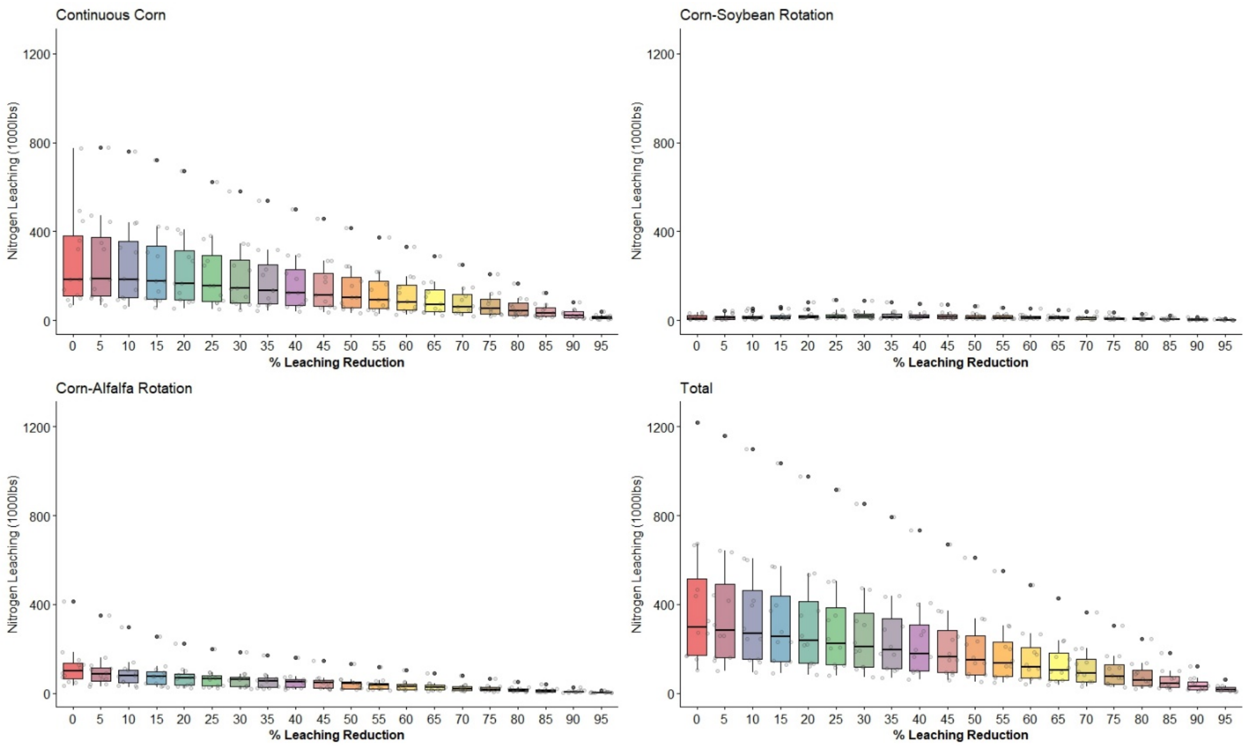


Figure 5: Behavior Adjustments of Leaching Cap Policies. Boxes represent the first quartile, median, and third quartiles of the distribution of measured data (gray points) for each modeled year (2003–2014); whiskers represent 1.5× the interquartile range.

(a) Nitrate Leaching



(b) Nitrous Oxide Emission

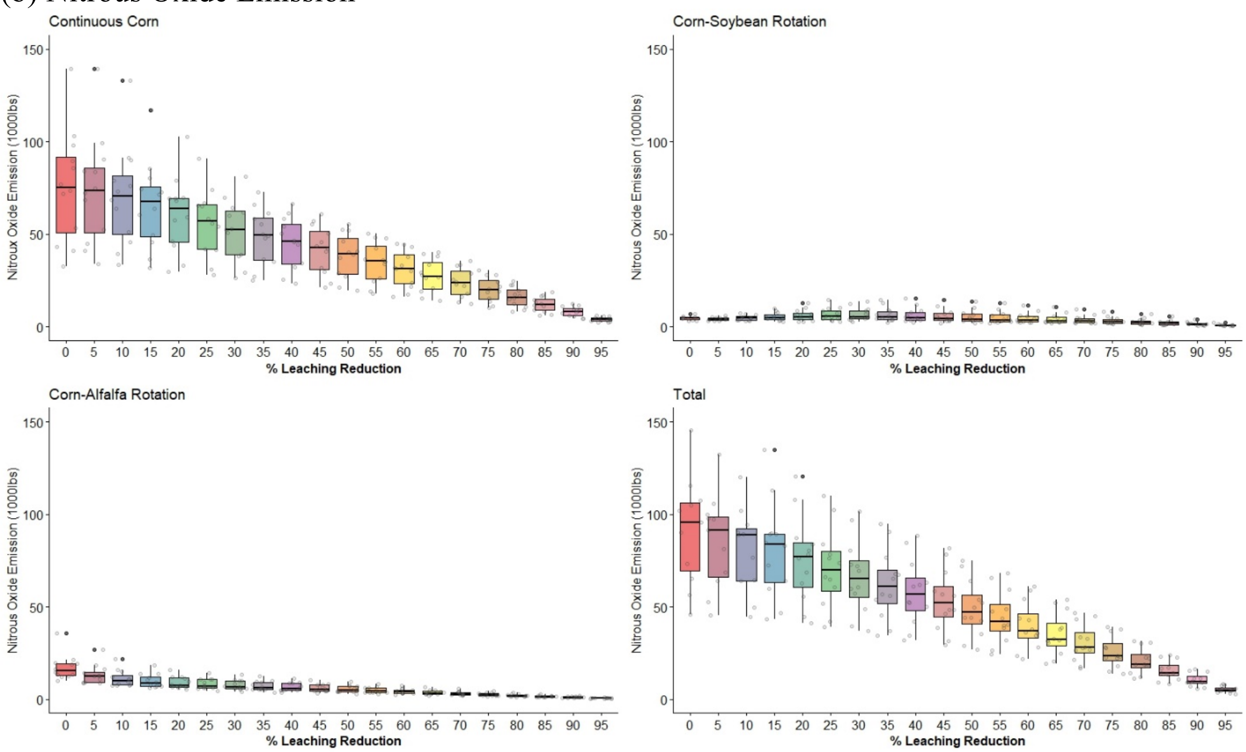


Figure 6: Environmental Pollution Levels of Leaching Cap Policies. Boxes represent the first quartile, median, and third quartiles of the distribution of measured data (gray points) for each modeled year (2003–2014); whiskers represent 1.5× the interquartile range.

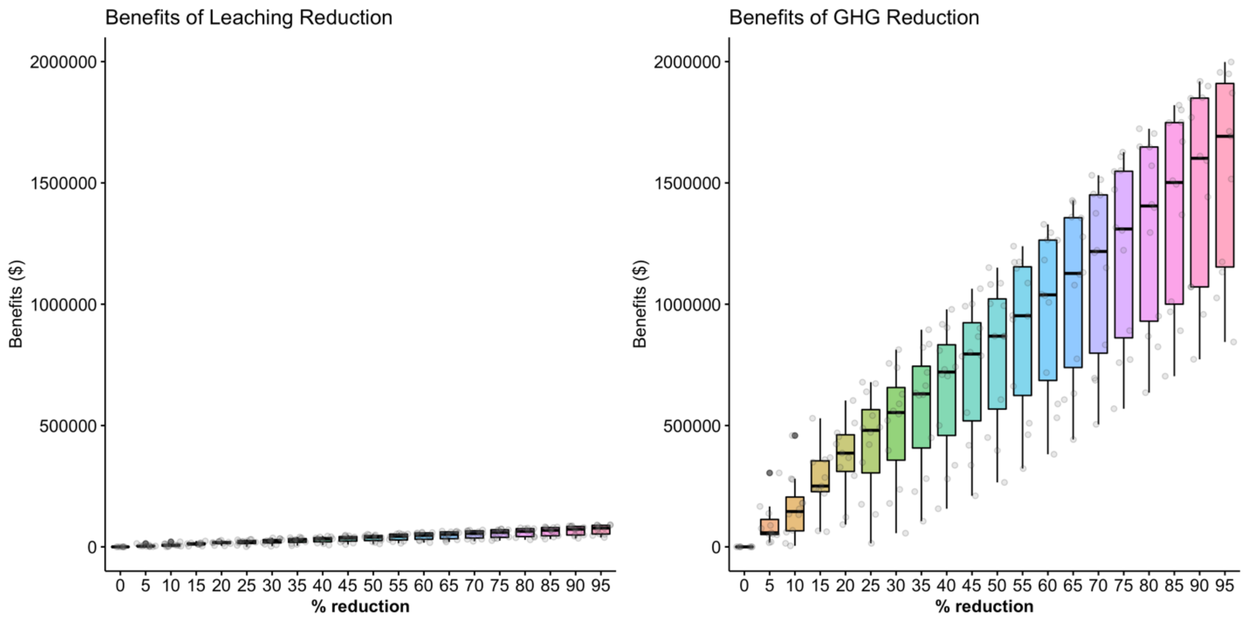


Figure 7: Monetary Value of Leaching and nitrous oxide emission Reductions. Boxes represent the first quartile, median, and third quartiles of the distribution of measured data (gray points) for each modeled year (2003–2014); whiskers represent 1.5× the interquartile range.

Table 1: References of 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%
Soybean							
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 2: Factor Costs and Factor Shadow Costs

Crop	$c_{i1} + \bar{\lambda}$ ($/acre)	λ_{i1} ($/acre)	c_{i2} ($/acre)	λ_{i2} ($/acre)
Continuous Corn	416.04	-271.03	0.70	-0.01
Corn Following Soybean	411.11	-262.54	0.84	-0.59
Soybean Following Corn	306.94	-157.44	2.88	-2.88
Corn First Year Following Alfalfa	415.30	-256.40	2.81	-2.31
Corn Second Year Following Alfalfa	415.33	-246.79	0.86	-0.75
Corn Third Year Following Alfalfa	416.04	-242.72	0.70	-0.65
Alfalfa First Year Following Corn	307.62	-129.33	6.40	-6.40
Alfalfa Second Year Following Corn	253.58	-22.49	5.47	-5.47
Alfalfa Third Year Following Corn	253.58	-26.14	5.47	-5.47

Table 3 Quantification of co-benefits across 2003-2014

Water Policy	Nitrous Oxide Emission Reduction (lbs)	Benefits of Nitrous Oxide Emission Reduction ($)	Lost Farm Profits ($)	Benefit-Cost Ratio without Co-benefits	Benefit-Cost Ratio with Co-benefits
5% Reduction	5,487	85,036	-1,469,445	-0.0026	-0.0605
10% Reduction	12,071	162,338	-1,301,510	-0.0057	-0.1304
15% Reduction	17,202	246,303	-1,010,013	-0.0111	-0.2549
20% Reduction	22,003	337,196	-614,088	-0.0250	-0.5741
25% Reduction	25,940	423,186	-111,359	-0.1727	-3.9729
30% Reduction	28,617	501,982	482,814	0.0473	1.0870
35% Reduction	33,351	573,732	1,144,593	0.0228	0.5240
40% Reduction	37,365	647,410	1,865,750	0.0158	0.3628
45% Reduction	41,339	726,498	2,647,526	0.0125	0.2869
50% Reduction	45,595	803,324	3,501,644	0.0104	0.2398
55% Reduction	49,899	885,030	4,446,855	0.0090	0.2081
60% Reduction	54,147	970,077	5,510,406	0.0080	0.1840
65% Reduction	58,985	1,052,447	6,724,266	0.0071	0.1636
70% Reduction	63,339	1,135,634	8,112,149	0.0064	0.1464
75% Reduction	67,776	1,219,965	9,691,577	0.0057	0.1316
80% Reduction	72,287	1,306,536	11,528,257	0.0052	0.1185
85% Reduction	76,820	1,394,570	13,739,503	0.0046	0.1061
90% Reduction	81,497	1,483,891	16,562,562	0.0041	0.0937
95% Reduction	88,765	1,574,058	20,646,212	0.0035	0.0797

Table 4 Policy Tipping Point for Correcting Over-fertilization

Year	Optimal Leaching Level (lbs)	Policy Threshold (Reduction in leaching)
2003	103,767	32.3%
2004	229,840	29.1%
2005	71,875	31.5%
2006	174,560	36.1%
2007	424,682	36.3%
2008	563,725	16.4%
2009	137,552	19.1%
2010	909,499	25.5%
2011	199,516	26.3%
2012	276,976	40.4%
2013	345,380	21.3%
2014	133,164	20.3%
Mean	297,545	27.9%

Appendix S1. Parameter estimates for the Mitscherlich-Baule production functions used to calibrate yield function

	α_i	β_{i0}	γ_i	β_{i1}	β_{i2}
Continuous Corn	-	126.765	0.422	0.014	0.005
Corn Following Soybean	-	38.972	3.426	0.026	-9.088
Soybean Following Corn	55.093	-	-	-	-
Corn First Year Following Alfalfa	-	2.0574	80.943	0.041	-37.943
Corn Second Year Following Alfalfa	-	2.990	56.449	0.038	-56.456
Corn Third Year Following Alfalfa	-	4.950	34.099	0.029	-78.982
Alfalfa First Year Following Corn	4.470	-	-	-	-
Alfalfa Second Year Following Corn	5.828	-	-	-	-
Alfalfa Third Year Following Corn	5.734	-	-	-	-

Appendix S2. Parameter estimates and significances tests for the functions used to calibrate nitrate leaching function for continuous corn

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S3. Parameter estimates and significances tests for the functions used to calibrate nitrate leaching function for corn following soybean

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S4. Parameter estimates and significances tests for the functions used to calibrate nitrate leaching function for corn first year following alfalfa

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S5. Parameter estimates and significances tests for the functions used to calibrate nitrate leaching function for corn second year following alfalfa

	β_{i0}	β_{i1}	β_{i2}
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

Appendix S6. Parameter estimates and significances tests for the functions used to calibrate nitrate leaching function for corn third year following alfalfa

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S7. Parameter estimates and significances tests for the functions used to calibrate nitrate emission function for continuous corn

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S8. Parameter estimates and significances tests for the functions used to calibrate nitrate emission function for corn following soybean

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S9. Parameter estimates and significances tests for the functions used to calibrate nitrate emission function for corn first year following alfalfa

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S10. Parameter estimates and significances tests for the functions used to calibrate nitrate emission function for corn second year following alfalfa

	$\boldsymbol{\beta_{i0}}$	$\boldsymbol{\beta_{i1}}$	$\boldsymbol{\beta_{i2}}$
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

Appendix S11. Parameter estimates and significances tests for the functions used to calibrate nitrate emission function for corn third year following alfalfa

	β_{i0}	β_{i1}	β_{i2}
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