Trade-offs Among Increasing Farm Net Returns and Reducing Emissions of Nitrogen, Phosphorus, Greenhouse Gas Equivalents, and Ammonia in a Dairy Farm

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Abstract: Agricultural producers are under pressure to reduce the environmental impacts of their activities. Most of the environmental concerns related to animal agriculture have focused on water quality, but air quality issues have become an increasing concern. Due to the transfer of nutrients between air, water, and soil, it is important to consider the role of air pollution in aggravating water quality. In this regard, we conduct a multi-objective ϵ-constraint optimization analysis to evaluate trade-offs among reduction of multiple pollutants including nitrogen, phosphorus, greenhouse gas (GHG) and ammonia on a representative dairy farm. We optimize each of the objective functions (net returns, and reductions of nitrogen, phosphorus, ammonia, and greenhouse gas), in turn, using the other objective functions as constraints. By changing the RHS of the constrained objective functions, the efficient solutions can be obtained. The farm entails crop production, livestock production (dairy and broiler) and manure management activities. We expect that improving dairy cattle diet focusing on nutrient requirements will reduce pollutants at the lowest cost. In addition, we predict that the reduction in GHG and ammonia emissions as well as N and P loadings will demonstrate a diminishing return to increasing cost.

The agricultural sector plays a significant role in water and air pollution especially in areas such as the Chesapeake Bay that supports the activities of over 13.6 million people [1]. Based on the reports of Chesapeake Bay TMDL Tracker (Tracker, 2017), the total nitrogen (N) and phosphorus (P) loadings from non-regulated agricultural operators of Pennsylvania were about 62.47 and 2.43 million pounds, in 2016 respectively. These loadings are much higher than those from other sectors such as forests, non-regulated stormwater facilities and point source pollutants with 21, 9 and 6.95 million pounds of N loading and 0.38, 0.45 and 0.53 million pounds of P loading, respectively. In addition, this sector made a contribution of 9 percent of total U.S. Greenhouse Gas (GHG) emissions in 2015 [2]. On the other hand, many studies show that the cost of pollution reduction in the agricultural sector is less than in other sectors (Stephenson and Shabman, 2017). Thus, mitigating the detrimental effects of water and air pollution of the agricultural sector is both an important issue and an effective solution, which needs to be addressed properly.

Agricultural producers are under pressure to reduce the environmental impacts of their activities. To reduce water and air pollution, the Federal government established the Clean Water Act (CWA) and Clean Air Act (CAA) in 1972 and 1975, respectively. The Total Maximum Daily Load (TMDL) program, established as part of the Clean Water Act, provides for setting maximum allowable pollutant loads for watersheds in order for them to achieve their designated uses. The U.S. Environmental Protection Agency (USEPA) established a TMDL for the Chesapeake Bay watershed in 2010 to set pollution limits necessary to meet water quality standards. This TMDL imposes a 25 percent reduction in nitrogen loading and a 24 percent reduction in phosphorus loading (USEPA, 2010). Most of the environmental concerns related to animal agriculture have focused on water quality, but air quality issues have become an increasing concern (Gay and Knowlton, 2005). Due to the transfer of nutrients between air, water, and soil, it is important to consider the role of air pollution in aggravating water quality. However, air pollution itself is an important issue as well. Most of the GHG emitted from agriculture

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[1] Addressing Nutrient Pollution in the Chesapeake Bay. https://www.epa.gov/nutrient-policy-data/addressing -nutrient-pollution-chesapeake-bay

[2] Inventory of U.S. GHG Emissions and Sinks: 19902015 (published 2017) https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2015

comes from livestock, especially dairy and beef cattle (EPA, 2016). A comprehensive analysis of a whole farm system is needed to obtain a better determination of what happens to livestock emissions and how such emissions can be controlled cost effectively.

The scope of this study is the extended farm boundary. All operations such as crop production, livestock production, and manure management are considered in the analysis as well as activities for purchasing required feeds and selling additional by-products. Pollution associated with these activities is also considered including, CO_2 equivalent greenhouse gas. Crop production includes planting, harvest and selling activities.

These activities can be done with different agricultural Best Management Practices (BMPs) to control nutrient pollution. Dairy production includes feeding (planted and purchased feeds) and manure production. Manure management encompasses gathering, storing, processing and spreading activities.

One of the major barriers to effective pollution reduction is the cost of mitigation strategies. These costs make it less desirable for operators to comply with pollution control practices. For instance, in crop production, the strategies defined as best management practices (BMPs) include buffers, conservation tillage, cover crops, and nutrient management.

Dairy production strategies to mitigate pollution include diet optimization. As White (2016) shows, improving energy and protein use efficiency of dairy cattle could potentially reduce GHG emissions without sacrificing profitability. Moreover, as Moraes et al. (2018) state augmenting the efficiency of an expensive dietary nutrient such as N not only increases the economic competitiveness of the dairy industry but also reduces the environmental impacts.

Manure handling, storage, and application contribute to GHG and ammonia emissions. As Boesch et al. (2001) state, about 60 percent of N inputs into the Bay from Maryland Eastern Shore come from agricultural sources, of which about half are from animal manure. Thus, manure management systems can significantly contribute to pollution reduction, especially in the Chesapeake Bay area.

Table 1 summarizes the sources of each type of pollution on a farm. While White's (2016) study evaluated the important role of diet management in controlling air pollution, the relative role of manure management in reducing air and water pollution was not addressed. Yet the type of manure management system could have important implications for the costs of reducing air and water pollution.

Most of the studies in dairy production emphasized management of a single target such as controlling ammonia emission or minimizing N excretion. However, addressing these single target goals often results in an increase in other important environmental metrics. (White, 2016). Life cycle analysis often focuses solely on GHG emissions (Thoma et al., 2013) while ignoring potential trade-offs with other environmental impacts. Moreover, as Thoma et al. (2013) suggested, nutrient management strategies on the dairy farm that link inorganic fertilizer use with the application of manure for crop production should be integral to any GHG reduction approach.

Several studies (Tozer and Stokes, 2001, White, 2016, Thoma et al., 2013,?) emphasize a multi-objective analysis of pollution reduction whereby improving the level of one objective may come at the price of worsening other objectives. Such trade-offs better represent the complex nature of environmental impacts.

The objective of this study is to evaluate trade-offs between profits, GHG emissions, N and P loadings and ammonia emissions on a representative dairy farm. Understanding how the pollution reduction strategies affect farm profit enables us to reduce GHG and ammonia emissions and N and P loadings from a particular dairy farm in a cost-effective manner.

We assume that the farmer is a rational decision-maker who seeks to maximize profit. Also, we assume the dairy farm located within Mahantango Watershed in Northumberland County, Pennsylvania represents varying dairy farms in the mid-Atlantic region in terms of optimal responses to water and air quality constraints. We expect that implementing practices for the crop, dairy and manure production to control N, P, and ammonia loadings and GHG emissions will reduce profit. In addition, we expect the relationship between reduction in GHG and ammonia emissions, N and P loadings and profit demonstrates a diminishing return to increasing cost. Furthermore, we hypothesize that improving dairy cattle diet specifically focusing on N and P efficiency will result in the greatest reduction in GHG and ammonia emissions and N and P loadings for a given level of cost (profit reduction) based on the findings of

Moraes et al. (2018) and Feng et al. (2015). We hypothesize that manure management and crop BMPs are of secondary importance for pollutant reduction.

Theoretical Background

The term " multiple objective programming" takes several conflicting definitions in the literature (McCarl and Spreen, 1997). Multi-objective programming has been used to refer to only the class of problems with weighted or unweighted multiple objectives, whereas goal programming has been used to refer to multiple objective problems with target levels. In this regard, we can categorize different multi-objective optimization methods into three broad categories: those involving no tradeoff such as lexicographic models (McCarl and Spreen, 1997), those involving tradeoffs among objectives using procedures such as multi-objective linear optimization (CARVALHO et al., 2012) and mixed integer programming (MIP) (Gibbons et al., 2005), and those involving risk methods such as safety first (Qiu et al., 2001) and Target MOTAD formulation (Teague et al., 1995). In this study we follow the second approach using the ϵ-constraint method (Mavrotas, 2009).

In the original version of this method, one of the objective functions is optimized using the other objective functions as constraints. By changing the RHS of the constrained objective functions, the efficient solutions can be obtained (Mavrotas, 2009). However, the Augmented and improved Augmented ϵ-constraint method introduced by Mavrotas (2009) and Mavrotas and Florios (2013), respectively, are suitable for Multi-Objective Integer Programming. Although this method demands computational effort, it has several advantages in comparison with the weighting method (Mavrotas, 2009): including producing non-extreme efficient solutions, insensitivity to objective functions with different scales, and ability to manage a large number of efficient solutions.

In this study, we use a multi-objective optimization to evaluate profit maximizing levels of reducing GHG and ammonia emissions and N and P loadings. Figure 1 represents the whole farm optimization model. The mathematical model selects among different crops subject to land, machinery, rotation, manure spreading, and other constraints.

For crop production, we include cover crops, buffers, reduced tillage, and nutrient management which reduce N and P loadings. In dairy production, the model selects among different feed options subject to milk production, nutrient requirement, maximum dry matter intake (MDI), and cow group specification (the number in population, time in system) constraints. Based on a previous study by Feng et al. (2015), we consider diet optimization as a strategy with the focus on N and P requirements for dairy cattle.

Finally, for manure management part, the model estimates the manure produced by the dairy cattle and the GHG and ammonia emission and N and P loadings from the manure management strategy.

We use the following multi-objective mathematical model:

$$\begin{aligned} Max \quad & (f_1(x), f_2(x), ..., f_n(x)) \\ s.t. \quad & x \in S, \end{aligned} \tag{1}$$

where x is the vector of decision variables and $f_1(x), f_2(x), ..., f_n(x)$ are n objective functions and S is the feasible region. Then, the formulation of ϵ-constraint method will be as (Mavrotas, 2009):

$$\begin{aligned} Max \quad & (f_1(x)) \\ st \quad & f_2(x) \geq e_2, \\ & f_3(x) \geq e_3, \\ & \vdots \\ & f_n(x) \geq e_n, \\ & x \in S, \end{aligned} \tag{2}$$

where e_i is the variation of the RHS of the constrained objective functions.

In order to properly apply the ϵ-constraint method, we need to have the range of $n - 1$ objective functions that will be used as constraints. The common approach to calculate these ranges is using the payoff table. Payoff table is obtained by the results from the individual optimization of n objective functions. We use a lexicographic optimization to generate the pay-off table, in which we optimize each objective given the optimal amount of the previous objective(s) as a constraint. After calculation of the pay-off table we divide the ranges into four equal intervals and then use these five grid points as the values of each e. If all $n-1$ objective functions are binding we will have an efficient solution, otherwise, the result would be a weakly efficient solution (Mavrotas, 2009). In order to avoid generating weakly efficient solutions, Mavrotas (2009) proposes a transformation for the objective function constraints to force the model to produce only efficient solutions. Therefore, the Augmented ϵ-constraint will be formulated as:

$$\begin{aligned} Max \quad & (f_1(x) + \epsilon \times (s_2 + s_3 + ... + s_n)) \\ & st \quad f_2(x) - s_2 = e_2, \\ & f_3(x) - s_3 = e_3, \\ & \vdots \\ & f_n(x) - s_n = e_n, \\ & x \in S, \quad and \quad s_i \in \mathbb{R}^+ \end{aligned} \tag{3}$$

where ϵ is an adequately small number (usually between 10^{-3} and 10^{-6}) and s_i is the slack or surplus variables for the ϵ-constraints. Moreover, in order to avoid any scaling problems, Mavrotas (2009) recommends replacing the s_i in the second term of the objective function by $\frac{s_i}{r_i}$ where r_i is the range of the $i-th$ objective function (as calculated from pay-off table).

$$
\begin{aligned}
Max \quad (f_1(x) + eps \times (\frac{s_2}{r_2} + \frac{s_3}{r_3} + \ldots + \frac{s_n}{r_n})) \\
st \quad f_2(x) - s_2 = e_2, \\
f_3(x) - s_3 = e_3, \\
\vdots \\
f_n(x) - s_n = e_n, \\
x \in S, and \ \ s_i \in \mathbb{R}^+
\end{aligned}
\tag{4}
$$

The first objective is profit maximization which includes profit from crop production, net revenue of livestock production, profit from selling crops and manure, minus costs of livestock production, crop BMPs, manure storage and application. The definitions of elements used in equations as well as the parameters of the objective functions are shown in Table 2 and Table 3, respectively. The mathematical equation takes the form of:

$$
\begin{aligned}
f_1 = -\sum_f x(f) * TC(f) - \sum_f P(f) * BPR(f) + \sum_f S(f) * SPR(f) + x(broiler) * NRL \\
+ \sum_u S(u) * MSP(u) - \sum_u A(u) * MAC(u) - \sum_n C(n) * NPR(n) + Tmilk * MPR \\
- \sum_c x(c) * FC + \sum_c x(c) * GR - TBMPC
\end{aligned}
\tag{5}
$$

Where

$x(f)$: Hectares of crops produced

$P(f)$: Kg of feeds purchased

$S(f)$: Kg of each on-farm feed sold

$x(broiler)$: Number of the broiler houses

$S(u)$: Units of manure sold

$A(u)$: Units of manure applied on the farm

$C(n)$: Kg of commercial fertilizer used on the farm

$Tmilk$: Kg of total milk produced

MPR: Price (\$ per kg) of milk

$x(c)$: Number of cows at each category

FC: Fixed cost per cow

GR: Gross revenue per cow

$TBMPC$: Total BMP costs (see Equation 10)

The second objective seeks to reduce the GHG emission of the total farm.

$$f_2 = GHG(B) - TGHG \tag{6}$$

Where,

$GHG(B)$: The total GHG emitted without any environmental constraints

$TGHG$: Total GHG emitted under the constrained scenario

The third objective is the ammonia emission reduction:

$$f_3 = Am(B) - TAm \tag{7}$$

Where,

$Am(B)$: The total ammonia emitted without any environmental constraints (Baseline scenario)

TAm: Total ammonia emitted under the constrained scenario

The fourth objective function is N loading reduction:

$$f_4 = \sum_f (\sum_b ((1 - Nr(b)) \times x(f, b))) \tag{8}$$

Where

$x(f)$: Hectares of crops produced $Nr(b)$: See Table 2

And, the last objective function minimizes the P loading:

$$f_5 = \sum_f (\sum_b ((1 - Pr(b)) \times x(f, b))) \tag{9}$$

Where

$Pr(b)$: See Table 2

These objectives are constrained by machinery, livestock facility, crop rotation, manure disposal and spreading, nutrient requirements for crops and livestock, maximum dry matter intake and milk yield.

The baseline scenario is the single-objective optimization of each of the objectives including profit maximization, and minimization of GHG emission, ammonia emission, N loading and P loading. The multi-objective scenario includes optimization of profit and reduction of GHG emission, ammonia emission, and N and P loadings.

The expected trade-off between N and P loading reduction is a competing relationship based on a previous study by Tozer and Stokes (2001). They also argue that the N loading reduction has a competing relationship with cost, but P loading reduction does not show any specific relationship with cost as strongly as N. To the best of our knowledge, other pollutant combinations have not been studied as multiple pollutants so there is less information about the trade-offs. However, we expect that the GHG and ammonia emissions reductions will show a supplementary relationship over a range from the vertical axis to point a and from the horizontal axis to point b as shown in Figure 2 with a competitive relationship between points a and b.

The study is carried out in the WE-38, a 7.3 km2 sub-watershed of Mahantango Watershed, located in Northumberland County, Pennsylvania. We use the data on crop yields, and crop N and P loading generated by SWAT-VSA (Wagena et al., 2018, Easton et al., 2008, Collick et al., 2015). The model will be run using the Generic Algebraic Modeling System (GAMS; https://www.gams.com/). The model simulates a one-year time frame.

EMPIRICAL MODEL

In this section, we present model inputs, constraints, and environmental modeling framework. We divide the activities within the dairy farm into three main activity groups including crop production, dairy production, and manure management. In addition, to be able to evaluate the results from ϵ-constraint multi-objective optimization, first, we will get the results from simple non-linear (NLP) profit maximization with respect to environmental constraints on nitrogen, phosphorus, ammonia, and GHG.

1 Model Inputs

1.1 Crop Production

Formulation of the crop production using Non-Linear Programming (NLP) enables the model to select among alternative on-farm and off-farm feeds subject to land, machinery, rotations, BMPs, and animal feed requirements. Total land available for crop production and pasture is 400 and 23 hectares, respectively. The allowable on-farm crops and their characteristics are shown in Table 4. On-farm crops can be both sold and purchased, however, the purchasing price is assumed to be 10 percent more than selling price, in order to reflect marketing margins required by feed suppliers. In addition, machinery and labor constraints limit the production of corn, full-season soybeans, double-cropped soybeans, and wheat to 231, 186, 191, and 240 hectares, respectively.

Using set notation, we created multi-dimensional variables. Feed variables are dimensioned on the type of crop, rotation and BMPs employed in the production of that feed. Table 3 lists all the sets used in the model, their elements and subsets. Crop BMPs are used to reduce nutrient loading into surface and ground water. The effectiveness of these BMPs, as well as their annual costs, are presented in Table 5. Total diet cost for cows consists of the cost of purchasing off-farm feeds. Costs of farm produced feeds are charged to the crop activity.

These BMPs are among the most cost-effective practices for the Chesapeake Bay watershed (Simpson and Weammert, 2009, Best Management Practices, 2015). Total BMP cost is calculated based on the summation of costs of all BMPs used to grow a specific crop:

$$\sum_{b}\sum_{rt}\sum_{f}(x(rt,f,TILL,CC,NM,BUF)*BMPcost(TILL,BUF,CC,NM)) \tag{10}$$

where,

$x(rt,f,TILL,CC,NM,BUF)$: hectares of crop produced under each rotation and BMP.

Using cover crops, nutrient management plans, continuous no-till and off-stream watering results in nutrients loading reduction from the area where they are applied, while stream buffers reduce nutrient loadings from upslope areas (Bosch et al., 2018). Machinery and labor constraints limit the cover crop planting to 372 hectares. The nutrient management is divided into tiers in which the effectiveness estimates for higher tiers is assumed to include the lower tier practices in place (Bosch et al., 2018). In addition, the maximum land available for stream buffers is 20% of the total buffer treatment area. Total hectares of land that could be retired as Conservation Reserve Program (CRP), should be at most 25% of the total land available.

Crop rotations considered in the model include continuous corn, corn-soybeans, two years corn-three years alfalfa, corn-two years alfalfa, corn followed by double-cropped wheat and soybeans, and continuous grass pasture. Rotations also include rye cover following corn or soybeans. Corn may be produced as grain or silage. Moreover, corn yields are increased 4, 8, and 11 percent when grown in rotation with soybeans, two years alfalfa, and three years alfalfa, respectively (Roth, 1996).

Crop nutrient requirements are defined based on crop nutrient removal per unit of yield and are met by legume N carryover, nutrients from manure spreading, commercial fertilizer applications (Curran and Lingenfelter, 2015), and ammonia deposition. The unit prices for each commercial fertilizer used including application are $1.76, 2.08, and 1.15 per kg of nitrogen, phosphorus, and potassium, respectively.

1.2 Livestock Production

Animal diet optimization is one method which helps to improve the production system, however, its potential environmental benefits have not been investigated well (White, 2016). We optimize the amount of feed required by category of dairy cows. There are five categories including one to four-year old cows as well as five-plus-year old cows. The decision variable is the number of cows kept which is dimensioned on the age of the cows in any month. The cow's population is calculated based on culling rate and the farm maximum capacity for dairy cows is assumed to be up to 80 cows.

The monthly diet optimization is formulated such that it selects alternative feeds to meet the nutrient requirements for phosphorus, calcium, metabolized energy and protein as the basic diet requirements. The nutrient requirements for cows were calculated based on Council et al. (2001). The nutrient requirements can be met via on-farm and off-farm feeds. For lactating cows (c_3, c_4, and c_5), the dry matter intake consists of 40 to 60 percent forages. In addition, there is a Maximum Dry Matter Intake (maxDM) level for each cow based on their age (Council et al., 2001). As stated by McCubbin et al. (2002) excess dietary N is excreted as manure that may contribute to nitrogen loading. In addition, Feng et al. (2015) state that there is a strong relationship between dietary P and manure P which makes dietary nutrient management a useful approach to reduce environmental impacts of dairy production.

Total milk production is assumed to be a function of the population of the cows that are lactating in each month times average milk yield per cow based on national average of 10.219 kg/305 d (APHIS, 2009). Fixed cost and gross revenue (excluding milk revenue) for dairy production are calculated based on Eberly and Groover (2011) \$2,676.71 and \$1,480.68 per head in 2017 U.S. dollars, respectively. Milk net revenue is assumed \$0.168 per pound based on Eberly and Groover (2011) calculations.

The broiler house has the capacity of 242,000 birds per year. The total gross revenue (not including revenues from broiler litter sales) and total variable costs are \$72,814 and \$17,330 per house in 2017 U.S. dollars, respectively (Eberly and Groover, 2011). This gives a total net revenue of \$55484 dollars per house per year. The farm is assumed to have a maximum of one broiler house. In addition, we assumed that feed for broilers is supplied by the poultry integrator.

1.3 Manure Management

Dairy and poultry manure is a source of nutrients for plants. Large quantities of nutrients can be recycled through crop production especially when multi-cropping systems are utilized (Newton et al., 2003). Manure management practices such as collection, storage (liquid and solid) and application, mostly depend on how dairy cattle are housed and vary with farm size (Gourley et al., 2012). As stated by Dairy (2007) 49.4 percent of the operations with liquid manure use slurry lagoons as their first treatment strategy. We assume this method as the manure management strategy for liquid manure. In addition, there is solid storage for solid manure production.

We assumed four different activities for manure management: manure production, storage, spreading and selling. The dairy cows produce 21.0875 thousand liters of liquid manure and 8.4125 mt solid manure per head, annually. A broiler house also produces 376 mt litter annually which includes manure excretion and litter bedding (Curran and Lingenfelter, 2015). All types of manures produced can be applied on the farm or sold. Broiler litter can be sold for an estimated price of $16.39 per mt (in 2017 dollars) (Pease et al., 2012), while dairy solid can be given away and dairy liquid can be given away if the exporting farm pays the costs of spreading. Dairy solid and litter spreading costs are $7.2 per mt while dairy liquid spreading costs are $2.1 per 1000 liters (in 2017 dollars) (Van Kooten et al., 1997).

1.4 Environmental Calculations

Nutrient management in livestock production protects air quality by reducing odors and nitrogen emissions (ammonia and oxides of nitrogen). Based on the N mass balance (Stephenson et al., 2013) prior to field application, the primary source of N loss is air emissions. Nitrogen can be emitted primarily as ammonia (NH_3) or as nitrous oxide (N_2O) at this stage. In general, there are two different strategies to reduce ammonia emission on the farm. First, the pre-excretion approach tries to reduce the amount of ammonia generated on the farm. Second, the post-excretion approach limits the ammonia emission by treating or managing the produced manure. The former strategy manipulates the animal's diet (Gay and Knowlton, 2005). For instance, optimizing N intake can theoretically reduce ammonia excretion 43 percent (Bussink and Oenema, 1998). The latter strategy includes several methods such as application of chemical amendments, separation of feces and urine, manure storage facilities and sub-surface application of manure through the use of injectors (Gay and Knowlton, 2005).

Reducing ammonia loss may increase nitrate leaching. To prevent this, we need to account for the complete N budget of the farm (Bussink and Oenema, 1998). Despite variations in emissions of both ammonia and nitrous oxide depending on temperature, wind and time spent on handling and storage (USDA, 1992), we estimated the ammonia emissions using EPA (2004) emission factors for the flush dairy barn and broiler house. Figure 3 shows the total ammonia emissions from dairy farm and broiler house at each stage (EPA, 2004). As shown in Figure 3 much of the ammonia emission occurs at manure management stage and storage in dairy production system (71% and 20%, respectively). Equation 11 was used to calculate the ammonia emissions at each stage, with an emission factor expressed as a percentage of N loss as ammonia.

$$TAm = (\sum_i N_i * EF_i) * 17/14 \tag{11}$$

Where,

N_i: N excreted/managed at every stage of manure management i

EF_i: ammonia emission factor at every stage i (Figure 3), and

17/14: NH_3/N conversion factor.

In general, we can categorize ammonia emissions from livestock into three stages, housing area emissions, handling and storage emissions, and land application emissions that are shown in Figure 3. In addition, as Loubet et al. (2009) state, 2 - 60% of ammonia emissions will be deposited within 2 km area of the emission source. In this regard, we assumed an average deposition of 31% in the model. Furthermore, between one-quarter to one-half of the deposited ammonia on cultivated land will be delivered to surface waters (Sheeder et al., 2002).). We assumed a one-third ratio meaning that about 10% of ammonia emissions is delivered as N to surface water.

The GHG emissions are divided into 4 different emissions including nitrous oxide, enteric methane, manure methane, and carbon dioxide emissions from crop production. Tier II methods of Eggleston et al. (2006) have been used for nitrous oxide emissions. These calculated emissions included all direct, leached and volatilized emissions (Equation 12). The definition and values of the scalars used in Equation 12 through Equation 16 are expressed in Table 6

$$\begin{aligned} TNO = \sum_{a,m}((NE_{a,m} * EF3 * \frac{44}{28} + NE_{a,m} * Fracleach * EF4 * \frac{44}{28} \\ + NE_{a,m} * Ef5 * FracVol * (44/28)) * pop_{a,m} * day_m) \end{aligned} \tag{12}$$

Where,

TNO: Total nitrous oxide produced on the farm in kg

$NE_{a,m}$: Total nitrogen excreted (kg for each cow category at each month). See Equation 13

$pop_{a,m}$: Population of each cow category at each month

day_m: Number of days in each month

$$NE_{a,m} = (\sum_f dmi_{a,m,f} * feednut_{f,CP} * 0.16 * 1000) - cnex_{m,c})/1000 \tag{13}$$

Where,

$dmi_{a,m,f}$: Dry matter intake for each cow category in each month from each feed (kg)

$feednut_{f,CP}$: Percentage of crude Protein in each feed

$cnex_{m,c}$: N intake that is retained in body for each cow category (g)

Based on the White (2016) recommendation, we used Moe and Tyrrell (1979) equations to calculate the enteric methane emissions. For the manure methane emissions, we used the same calculation as for nitrous oxide (Eggleston et al., 2006). Total methane emissions are shown in Equation 14, Equation 15 and Equation 16.

$$TMT = \sum_{a,m}(CH4e_{a,m} + CH4m_{a,m}) \tag{14}$$

Where,

TMT: Total methane production on farm (kg)

$CH4e_{a,m}$: Total enteric methane emitted (kg) for each cow category at each month

$CH4m_{a,m}$: Total manure methane emitted (kg) for each cow category at each month

$$\begin{split}CH4e_{a,m} = ((3.51 + 0.511 * \sum_f dmi_{a,m,f} * feednut_{f,NSC} + 1.74 * \sum_f dmi_{a,m,f} * HC_f \\ +2.65 * \sum_f dmi_{a,m,f} * Cell_f) * pop_{a,m} * days_m)/1000\end{split} \tag{15}$$

Where,

$feednut_{f,NSC}$: Percentage of nonstructural Carbohydrates in each feed

HC_f: Percentage of Hemicellulose in each feed

$Cell_f$: Percentage of Cellulose in each feed

$$CH4m_{a,m} = VS_{a,m} * pop_{a,m} * days_m * Bo * 0.67 * (MCF/100)/1000 \tag{16}$$

Where,

$VS_{a,m}$: Volatile solid excreted in kg for each cow category in each month. See Equation 17

$$\begin{aligned} VS_{a,m} = &((\sum_f dmi_{a,m,f} * feednut_{f,GE}) * (1 - DigE_{c,m})) \\ &+(0.04 * \sum_f (dmi_{a,m,f} * feednut_{f,GE})) * ((1 - AshC_{a,m})/18.45) \end{aligned} \tag{17}$$

Where,

$feednut_{f,GE}$: Gross Energy in each feed

$DigE_{c,m}$: Digestible energy consumed by each cow category in each month

$AshC_{a,m}$: Ash concentration in each cow category in each month

The GHG emissions from crop production included (CO_2) and (N_2O) emissions for on-farm crop production as well as GHG emissions from transporting off-farm feeds (White, 2016). We assumed that all grain traveled an average of 1000 km prior to being fed to cows, which is the half of the distance from the Midwest (the origin of most of the U.S. grain) to the East Coast (White, 2016). The sources of GHG calculations are Data and Statistics (2013) and Burek et al. (2014) and the total GHG emission from the farm is calculated using Equation 18. The total farm GHG emission is reported as (CO_2)-equivalent using CHANGE (2007) 100-yr warming potentials.

$$TGHG = \sum_f x(f) * CO_2(f) + \sum_f p(f) * CO_2(f) + CF_1 * TMT + CF_2 * TNO \tag{18}$$

Where,

$x(f)$: Kg of crop f produced on farm

$CO_2(f)$: kg of GHG emitted for production/transportation of each crop f

$p(f)$: Kg of off-farm feeds purchased

CF_1: CO_2-equivalent warming potential for methane

TMT: Total methane produced in kg (enteric and manure)

CF_2: CO_2-equivalent warming potential for nitrous oxide

TNO: Total nitrous oxide produced on farm in kg

Nitrogen and phosphorus loading for each crop as well as their yields were obtained using SWAT (Soil and Water Assessment Tool) model based on the characterizations of two sub-watersheds in WE-38 from previous studies (Bosch et al., 2018, Easton et al., 2008, Collick et al., 2015). Table 4 shows all loadings and emissions from crop production for each on-farm crop. To calculate total farm N and P loadings we used Equation 19 and Equation 20.

$$TNit = \sum_f x(f) * Nload(f) - f_3 \tag{19}$$

Where

$x(f)$: Hectares of crop f produced on farm

$N(f)$: N loaded (kg/ha) for each crop (see Table 4)

f_3: Total N reduction by BMPs Equation 8

$$TPhs = \sum_f x(f) * Pload(f) - f_4 \tag{20}$$

Where,

$x(f)$: Hectares of crop f produced on farm

$P(f)$: P loaded (kg/ha) for each crop (see Table 4)

f_4: Total P reduction by BMPs Equation 9

1.5 Pollution Reduction Scenarios

There are four different environmental objectives in this study: N reduction, P reduction, GHG reduction, and ammonia reduction. In the baseline scenario, we are maximizing farm total (crop, livestock and manure management) profit without any constraint on environmental impacts. The Chesapeake Bay TMDL imposes 25 and 24 percent reduction in N and P loading, respectively (USEPA, 2010), thus we defined the maximum level of 25 percent reduction for all pollutants. In order to have a better understanding of how the model will behave with respect to these reductions we evaluated incremental reduction scenarios for each individual pollutant.

2 Optimization framework

2.1 Simple NLP Optimization

The purpose of the simple NLP optimization is to maximize the total profit for the farm while considering individual reduction scenarios as constraints. The total farm profit is expressed in Equation 5.

2.2 ϵ-constraint Multi-objective Optimization

The ϵ-constraint model tries to maximize one objective function subject to constraints on other objectives with multiple right hand sides (RHS). The right hand sides for the constrained objectives come from the single optimization of each objective that generates the payoff table as shown in Table 7. All other model inputs including environmental calculations and limitations on farm products are the same as NLP optimization.

In order to construct the ϵ-constraint model, we first determine a set of K objective functions which in our case K includes, "profit", "nitrogen", "phosphorus", "ammonia", and "GHG". The direction of each objective function is specified as -1 for minimization and $+1$ for maximization. We develop the augmented objective function to avoid weakly efficient solutions as shown in Equation 21.

$$f = dirction(profit) * Z(profit) + \epsilon * (\sum_{k \neq profit} \frac{S_k}{r_k}) \tag{21}$$

where,

f: Auxiliary variable for the objective function

K: Set of objective functions includes, "profit", "nitrogen", "phosphorus", "ammonia", and "GHG"

$Z(k)$: The objective function variable

ϵ: Small number (10^{-3})

$S(k)$: Slack or surplus variables for the eps-constraints

$r(k)$: Range of the objective function (maximum -minimum)

The next step is to add constraints for other objective functions as shown in Equation 22.

$$Z(k \neq profit) - direction(k) * S(k) = RHS(k \neq profit) \tag{22}$$

where,

RHS: The right hand side of the constrained objective functions in ϵ-constraint

The next step is to define a loop in order to generate the payoff table by applying lexicographic optimization. After generating the payoff table, we need to define a set of grid points which in our case we defined 10 grid points by simply dividing the ranges specified by payoff table. Then, we allow the model to walk through the grid points by using a loop to maximize the objective function f. The results for the payoff table and grid points are discussed in the next section.

Results and Discussion

1 Analysis of the NLP Model

1.1 Evaluating Baseline Performance

The environmental output of the baseline scenario for the total production system is shown in Table 8. Total farm profit, dairy profit, total diet cost, and total milk production are \$458,352 \$34,021, \$10,761, and 449 mt, respectively. The total liquid and solid manure produced are 21.09 thousand litters and 8.41 mt per head per year. The optimum number of broiler houses is one with the total profit of \$61,646.64 per year. The total manure produced by broiler house is calculated as 376 mt that is sold.

The total crop profit is calculated \$907 dollars per ha per year. In the baseline scenario, no BMPs are used, so the total BMP cost for the baseline scenario is zero. No commercial fertilizer is spread on the farm. Continuous corn (grain and silage), and double cropped corn-soybean are the only rotations used in the baseline scenario. In addition, total corn grain and soybean produced on farm are sold, while the total corn silage produced on farm is fed to the cows. The diet ingredients for dairy cows are purchased as required except for the corn silage.

The diet for the baseline consists of corn silage, wheat middlings, and sunflower seeds with the share of 71%, 26%, and 3%, respectively. Similar to the baseline, corn silage and wheat middlings are determined as the two main feeds for most of the scenarios.

1.2 Maximizing Nitrogen, Phosphorus, Ammonia or GHG reduction

1.2.1 Nitrogen

The individual nitrogen reduction scenarios include 5 to 25 percent reductions. As we expect the total farm profit falls as the reduction increases. Ammonia, phosphorus, and GHG show remain unchanged up to 15 percent nitrogen reduction. However, they show a 5 to 15 percent reduction as nitrogen reduction rises to 20 and 25 percent (Figure 4). Total farm profit decreases with larger decreases occurring at 15 percent reductions and above as shown in Figure 5. The reason for this change is the reduction in the number of the cows by 13% from 15 to 25 percent nitrogen reduction. The total diet cost follows the same trend as total dairy profit and total number of cows.

The number of the broilers remains constant as nitrogen reduction increases, which results in the constant amount of the broiler litter produced and broiler profit. However, due to the fall in the number of dairy cows, milk production, solid manure, and liquid manure decreases.

Crop production profit shows decremental change due to changes in the crop production both in terms of the amount of each crop being produced and the BMPs used. Crop production falls 4.45% at 25 percent reduction. The results show that increasing nitrogen reduction up to 20 percent has no effects on the total land used, however at 25 percent reduction, the model is forced to grow less crops. The total BMP cost increases due to increase in using buffers and levels of nutrient management.

1.2.2 Phosphorus

The individual phosphorus reduction scenarios consist of 5 to 25 percent incremental reductions from baseline, in which as we expect the total farm profit (Figure 6) and the profit from crop production decrease as reduction increases. As shown in Figure 7, ammonia, and GHG reductions are uneven but increase steadily at 15 percent phosphorus reduction due to a change in the number of cows but the rate of increase declines as phosphorus reduction falls over 20 percent. The results indicate that production of corn grain and silage increases at 15 percent reduction, however total crop production falls at 20 and 25 percent reductions. For reductions of 15 percent the model increases number of dairy cows by 6.5%, however it decreases by 15.44 and 16.22 percent at 20 and 25 percent reductions, respectively.

Moreover, nitrogen loadings decline in concert with phosphorus loading decreases (Figure 7) which is the results of changes in both combination and amount of each crop produced on farm. In addition, the total BMP cost increases up to 15 percent reduction and decreases for reductions of 20 percent and more, due to reduction in total crop production.

Broiler house production stays at its maximum with $61647 profit similar to baseline. Broiler litter is also at its maximum production as in the baseline scenario. On the other hand, due to changes in the number of dairy cows, dairy profit and milk production rises up to 15 percent reductions and declines as reduction increases. Constraining phosphorus reduction forces the model to produce more corn grain and silage and less soybean. Consequently, more corn is available for dairy cows as feed, which results in an increase in the number of dairy cows.

1.2.3 Ammonia

The individual ammonia reduction scenarios include 5 to 25 percent reduction from baseline. In these scenarios, the total farm profit shows an expected decremental trend (Figure 8) with a sharp drop in profit after 20 percent. As shown in Figure 9, nitrogen, phosphorus, and GHG follows the same direction and remain constant up to 20 percent ammonia reduction, however, at 25 percent reduction the model decides to shut down the dairy and crop production showing the sensitivity to higher levels of ammonia reduction.

Broiler production is at a maximum with the same profit as the baseline up to 20 percent reduction in ammonia. Consequently, the amount of broiler litter produced remains constant. Dairy profit, total diet cost, and milk production decrease until 20 percent ammonia reduction. Dairy solid and liquid manure also show similar trends. Crop profit shows the same direction as total profit. Total BMP cost is zero during all individual ammonia reduction scenarios.

1.2.4 GHG

The individual GHG emission reduction scenarios consist of 5 to 25 percent emission reductions from baseline. In these scenarios, the total farm profit shows a decremental reduction as shown in Figure 10, while crop production profit shows an incremental increase. The total BMP cost for crop production is zero in all of these scenarios.

As shown in Figure 11, nitrogen and phosphorus reduction show a similar trend, and they both increase up to 20 percent GHG reduction. However, for GHG reduction over 20 percent, the amount of nitrogen and phosphorus reduction decreases due to a small change in the amount and type of crops being produced. Ammonia shows a similar trend as nitrogen and phosphorus up to 20 percent, while for GHG reduction over 20 percent, ammonia presents a sharp reduction of about 54 percent. This is mainly because of the reduction in the number of the dairy cows.

The broiler house produces at its maximum capacity with the profit of \$61,647, however, it falls to \$52,777 at 25 percent GHG reduction. In addition, all the broiler litter produced is used on farm. In order to avoid the GHG losses during spreading, dairy liquid and solid manure is being sold in all of these scenarios. The dairy profit and milk production show a decremental reduction. The overall trend is for diet cost to decrease due to reductions in the number of cows.

1.3 Analysis of Maximizing Nitrogen, Phosphorus, Ammonia and GHG reduction

In this section, we will analyze the incremental reductions in all environmental metrics altogether. These scenarios consist of reductions from 5 to 25 percent for nitrogen, phosphorus, ammonia, and GHG together. In these scenarios, as we expect, the total profit decreases as reductions increase. However, the trade-offs between profit and different pollutants reduction levels show an increasing forgone profit per unit of pollutant reduction as pollution reductions increase. The results confirm this relationship (Figure 12). Crop and dairy production profit decline along with total profit, while broiler profit remains constant. Total BMP costs increase up to 15 percent reduction, however it falls after 20 percent reduction due to reduction in total crop production.

The results also demonstrate that corn grain, soybean, and corn silage are the most profitable crops, respectively. Also, corn-soybeans, and continuous corn are the most profitable rotations for crop production, respectively. Furthermore, within all BMP alternative, nutrient management tier 1, tier 3, buffers and conservation tillage are also the most effective BMPs, respectively.

Dairy solid and liquid manure production fall as reductions increase. Similarly, milk production decreases. Total diet cost shows a jump at 10 percent reduction, however it falls at 15 percent reduction due to reduction in the number of cows. In addition, on farm manure spreading shows a high sensitivity to ammonia reduction, which is mainly because as the farm reduces more ammonia, it produces less animals and resulting in less manure available for spreading. Consequently, less ammonia is deposition on land.

Results for nitrogen and phosphorus reductions indicate negative high correlation with profit (-0.92 and -0.97, respectively). For GHG and ammonia the correlation is lower (-0.67 and -0.71, respectively). In comparison with the nitrogen and phosphorus reductions, we can conclude that GHG and ammonia reductions can be achieved by sacrificing less profit.

2 Analysis of the ϵ-constraint model

The results for the payoff table generated by ϵ-constraint optimizer are shown in Table 9. Row 1 shows results of maximizing profit and levels of each pollutant. Row 2 shows results of minimizing nitrogen and corresponding levels of profit and other pollutants. Rows 3 through 5 are read similarly with respect to minimizing phosphorus, ammonia, and GHG, respectively. The reason for the zeros in second to fifth row of the table is that the minimum values for the nitrogen, phosphorus, ammonia and GHG are zero when farm shuts down production of crop and livestock. Despite the fact that we run lexicographic optimization to generate payoff table, we allowed the model to cycle through the objective functions disregarding the lexicographic optimization, in case if it generated infeasible solution, which is the reason why we get zeros as value for the payoff table. The grid points used for the RHS of the constrained objective functions are generated by dividing the values from payoff table into 10 equal intervals (Table 7).

The results for this optimization show that the value for the profit is \$ 456,486 which is 0.4% less than the profit for the baseline scenario of NLP optimization. The results also show 0.7, 0.8, 3.4, and 10 percent reductions for nitrogen, phosphorus, ammonia, and GHG, respectively, relative to the baseline. Table 10 shows the results from ϵ-constraint optimization and their relative changes with respect to baseline. These results indicate that we can find opportunities to reduce all pollutants simultaneously to a certain level without sacrificing a significant amount of profit.

The results also confirm that the most profitable crops are corn grain, soybean, and corn silage respectively, with similar rotations as NLP optimization. No BMPs are used for crop production and all of the manure produced on farm is sold. The combination of the feeds for the diet is represented in Table 11. Generally, these feeds seems to be the most profitable ones because they were chosen as main feeds in NLP optimization as well as the ϵ-constraint optimization.

3 Summary and Conclusion

Because of the importance of water and air pollution abatement in the agricultural sector farmers need to make sure that they are able to manage the pollution reduction practices to be both feasible and inexpensive. Consequently, they seek to use different farm practices in order to maximize their profit while reducing pollution levels to reach a satisfactory level. This paper conducts two approaches to study the trade-offs associated with farm profit and reducing the most important pollutants generated by agricultural activities.

The results of this study show how profit changes with respect to different pollution reduction levels for multiple pollutants. Based on the results, we can conclude that the reduction of GHG and ammonia are less costly than nitrogen and phosphorus, respectively. Furthermore, livestock production management including diet optimization, manure handling and storage are the most important activities in order to reduce the pollutant loadings and emission, which needs to be more addressed by farmer.

Increasing marginal rate of substitution between profit joint pollution reductions, is confirmed by the results (Figure 12). The nitrogen and phosphorus reductions mainly depend on crop BMPs. However, for ammonia and GHG reduction farmers need to focus more on the diet optimization and manure handling. With diet optimization and proper usage of livestock manure, farmers can provide opportunities to reduce farm pollution and improve air and surface water quality. Furthermore, by showing the trade-off among water and air pollutant reduction on a dairy farm, this study can help policymakers to evaluate and coordinate the implementation of practices.

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Tables

Table 1: Sources of pollution on a farm. Source:(DOE, 2007, Feng et al., 2015)

Activity	Methane (CH_4)	Nitrous oxide (N_2O)	Carbon dioxide (CO_2)	Ammonia (NH_3)	Nitrogen (N)	Phosphorus (P)
Crop Production	×	✓	✓	×	✓	✓
Dairy Production	✓⋆	✓	×	✓	×	×
Broiler House	×	✓	×	✓	✓	×
Manure Management	✓	✓	×	✓	✓	✓

⋆ Enteric Fermentation

Table 2: Parameters of the model

Parameter	Units	Description
TC(f)	\$ per ha	Total cost of each crop excluding land and fertilizer
NRL(Broiler)	\$ per unit	Net revenue of a broiler house
BPR(f)	\$ per kg	Price of purchased crops
SPR(f)	\$ per kg	Price of sold crops
MSP(u)	\$ per unit	Price of sold manure
MAC(u)	\$ per unit	Cost of manure application
NPR(n)	\$ per kg	Price of commercial fertilizer used
N(f)	Kg per ha	Base N loading for each crop type
Nr(b)	Percent	N loading reduction of each BMP
Pr(b)	Percent	P loading reduction of each BMP
P(f)	Kg per ha	Base P loading for each crop type
$EF_{MMT}(k)$	Percent of N loss	Ammonia emission factor at every stage

Table 3: Definition and elements of sets and subsets in the model equations

Set	Set name	Elements	Element definitions
f	Feeds	See Table 4	includes on-farm and off-farm feeds
n	Nutrients	P, Ca, MP, ME	Nutrients available in feeds and required by cows
a	Animals	$c_1, ..., c_5$,Broiler	one to 5 years old cows and Broiler house
b	BMPs	subsets: TILL,CC,NM,BUF	Details are provided in Table 5
rt	Rotation	subsets: with/out cover crops	Crop rotation used in the production
m	Months	1,...,12	Months (January=1)

Table 4: On-farm crops. Source: Curran and Lingenfelter (2015), Data and Statistics (2013)

Crops	Cost^a (\$/ha)	Yield(mt/ha)	Price (\$/kg)	N loading (kg/ha)	P loading (kg/ha)	GHG emission (kg/kg)
Corn grain	952.18	7.87	0.24	2.90	10.68	0.39
Corn silage	1444.97	47.22	0.08	2.90	10.67	0.09
Soybean	487.57	2.02	0.70	2.20	7.80	0.42
Double-cropped Soy^c	41.15	1.21	0.70	1.85	8.72	0.42
Wheat	450.60	3.37	0.26	1.50	9.64	0.69
Alfalfa^b	708.91	8.99	0.19	1.71	2.59	0.44
Pasture	60.55	1	0.11	1.91	0.84	0.28

a (Curran and Lingenfelter, 2015)

b "Obtained by multiplying hay yield times 2.43 the ratio of hay dry matter (85%) to haylage dry matter" (35%)(Bosch et al., 2018)

c "Double crop soybean yield is 60% of full season soybean based on July 10 planting date" (Bosch et al., 2018)

Table 5: Costs per hectare (2017 $) and the effectiveness of Best Management Practices (BMPs)[a]

Best management practice	**N loading reduction (%)**	**P loading reduction (%)**	**Annualized cost/unit (2017$)**
Conservation tillage	10.5	10.8	115.890
Stream buffers[b]	32.0	39.0	491.75
Off-stream watering without fencing	5.0	8.0	76.22
Cover crops planted standard	24.0	5.0	85.613
Tier 1 Nutrient management both high and low till with manured	9.25	10.0	32.7
Tier 1 Nutrient management high till without manure; hay with nutrients	5.0	8.0	32.7
Tier 2 Nutrient management high till with manured	4.4	0	52.516
Tier 2 Nutrient management low till with manured	4.4	0	190.23
Tier 2 Nutrient management hay with nutrients	2.8	0	22.374
Tier 3 Nutrient management high till, low till with manured	2.8	0	2.798

a Effectiveness estimates are from Devereux (2014). Cost estimates are from bay program office. 2015 (2015) except for nutrient management (Bosch et al., 2018) and no-till which is based on a comparison of no-till and conventional till enterprise budgets (Curran and Lingenfelter, 2015).

b Grass buffer. Costs do not include land opportunity cost. Nutrient and sediment reductions are obtained from land use change to grass buffer and buffers effectiveness in filtering upslope nutrients. See text for further explanation.

Table 6: Scalars used for calculating environmental impact from dairy cow management

Scalar	Unit	Definition	Value
EF3	kg lost/kg excreted	Direct emission factor	0.009583
EF4	kg lost/kg excreted	Volatilized emission factor	0.01
EF5	kg lost/kg excreted	Leached emission factor	0.0075
Fracleach	%	Percent of managed manure nitrogen leached	28.105
Fracvol	%	Percent of managed manure nitrogen volatilized	17.3
BO	m3 CH4 / kg VS	Maximum emission rate	1
MCF	%	Average methane conversion efficiency	17.3

Table 7: Grid points for the RHS of the constrained objectives

	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	G_{10}
Nitrogen	1044.4	939.96	835.52	731.08	626.64	522.2	417.76	313.32	208.88	104.44
Phosphorus	3796.701	3417.03	3037.36	2657.69	2278.02	1898.35	1518.68	1139.01	759.34	379.67
Ammonia	51743.871	46569.48	41395.097	36220.71	31046.323	25871.94	20697.55	15523.16	10348.77	5174.387
GHG	1210120.52	1089108	968096.414	847084.4	726072.31	605060.3	484048.2	363036.2	242024.1	121012.1

Table 8: Environmental output of the baseline scenario

Metric	Value	Units
Nitrogen	2.62	kg/ha
Phosphorus	9.49	kg/ha
Ammonia	129.37	kg/ha
GHG	2.69	kg CO2-eq/kg milk

Table 9: Payoff table obtained by a ϵ-constraint optimizer

	Profit	Nitrogen	Phosphorus	Ammonia	GHG
Profit	458,352	1,044.40	3,796.70	51,743.87	1,210,120.52
Nitrogen	0.00	0.00	0.00	0.00	0.00
Phosphorus	0.00	0.00	0.00	0.00	0.00
Ammonia	0.00	0.00	0.00	0.00	0.00
GHG	0.00	0.00	0.00	0.00	0.00

Table 10: The results generated by ϵ-constrained optimization and the percentage change relative to baseline

	Value	% change
Profit ($)	456,486	0.4
Nitrogen loaded (kg/ha)	2.6	0.7
Phosphorus loaded (kg/ha)	9.4	0.8
Ammonia loaded (kg/ha)	125	3.4
GHG (kg per kg of milk)	2.6	10

Table 11: Combination of feed for cow's diet under ϵ-constrained optimization

Feed	Corn Gluten Meal	Grass Silage	Sunflower Seed	Wheat Middlings	Meat and Bone meal
Value (mt)	1.2	29.6	3.3	82.8	0.05

Figures

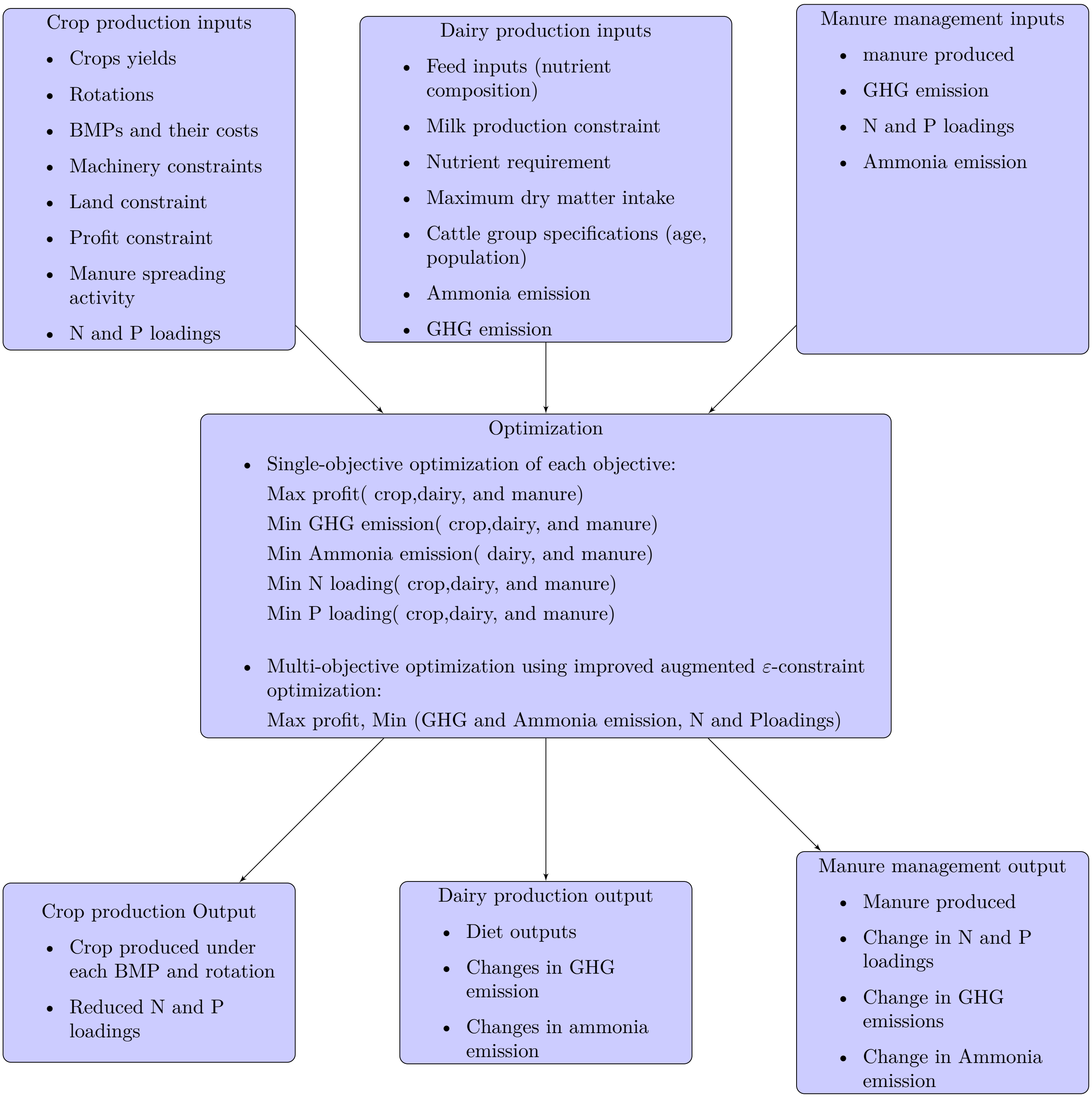


Figure 1: Farm-level optimization model

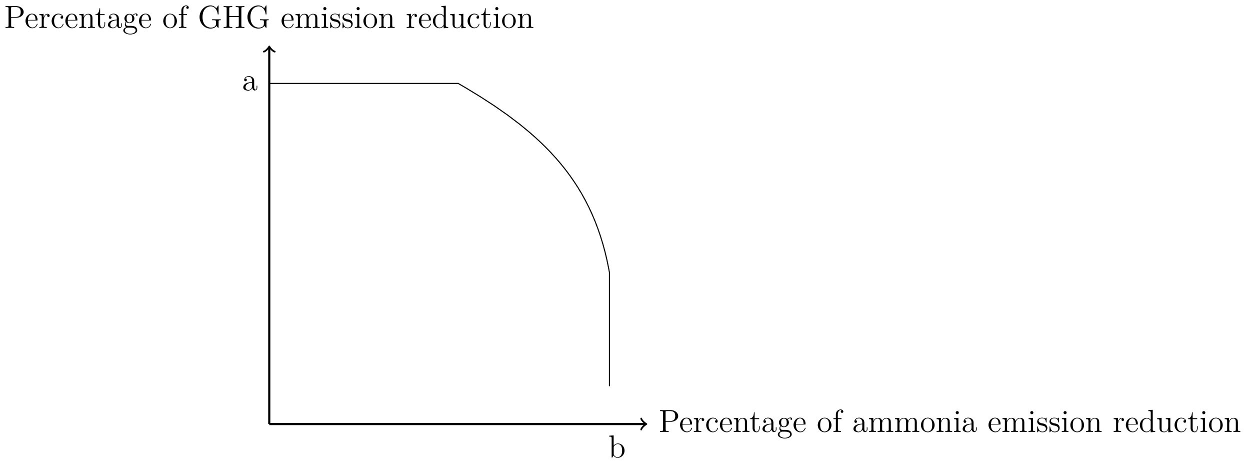


Figure 2: Expected trade-off between the percentage of GHG and ammonia emission reduction

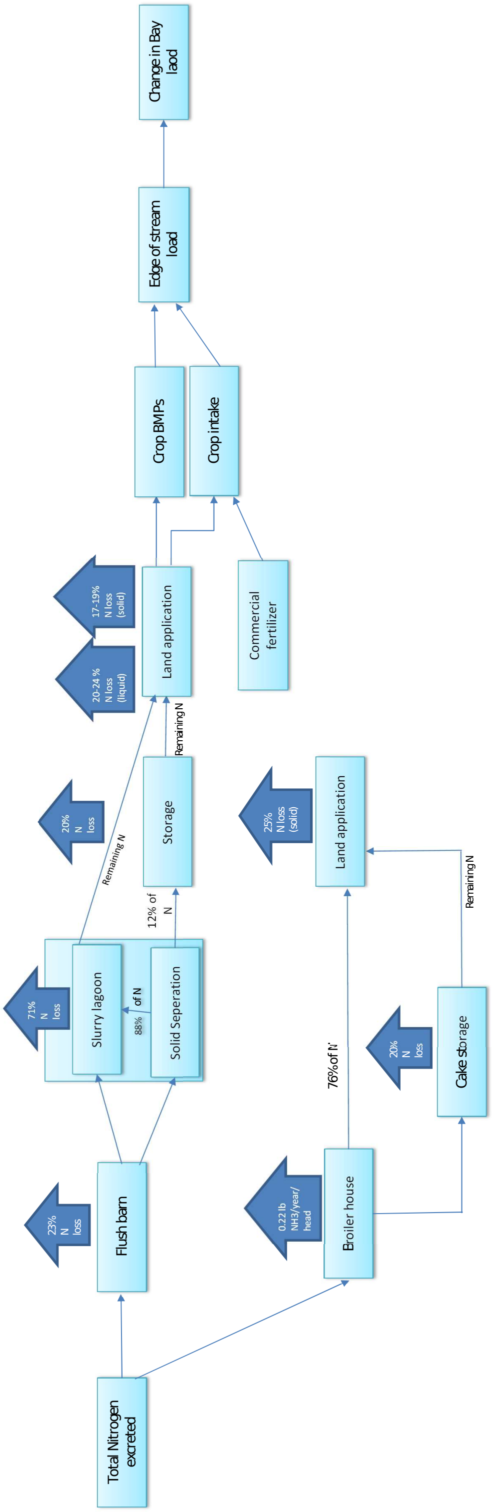


Figure 3: Total farm ammonia emissions (USEPA, 2004)

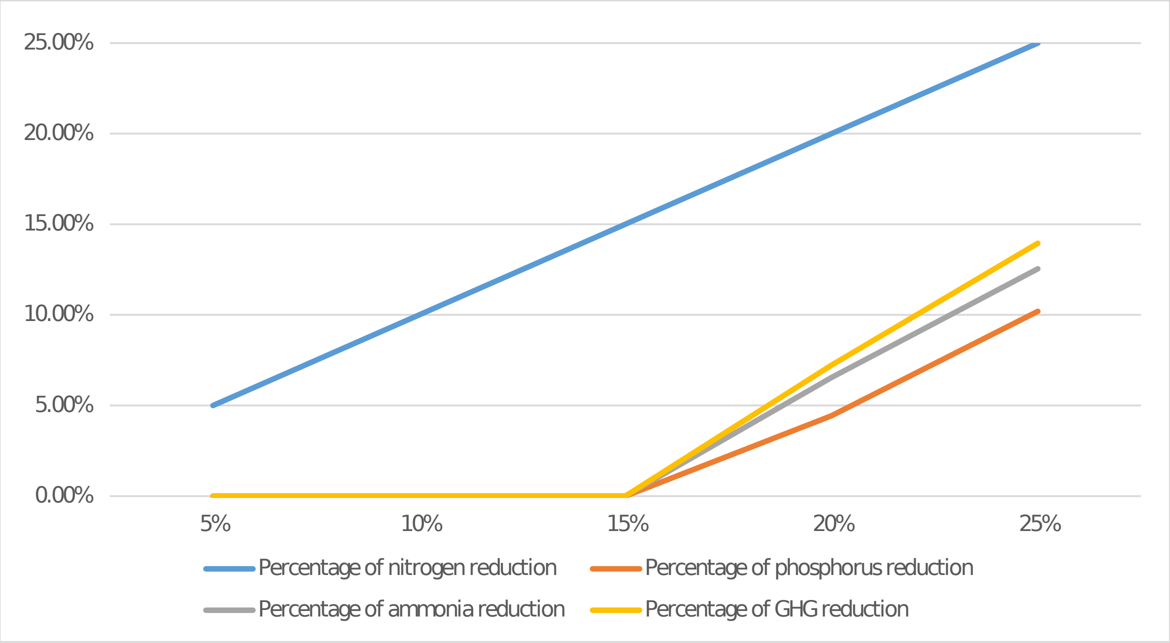


Figure 4: Environmental metrics reduction under individual nitrogen reduction scenarios

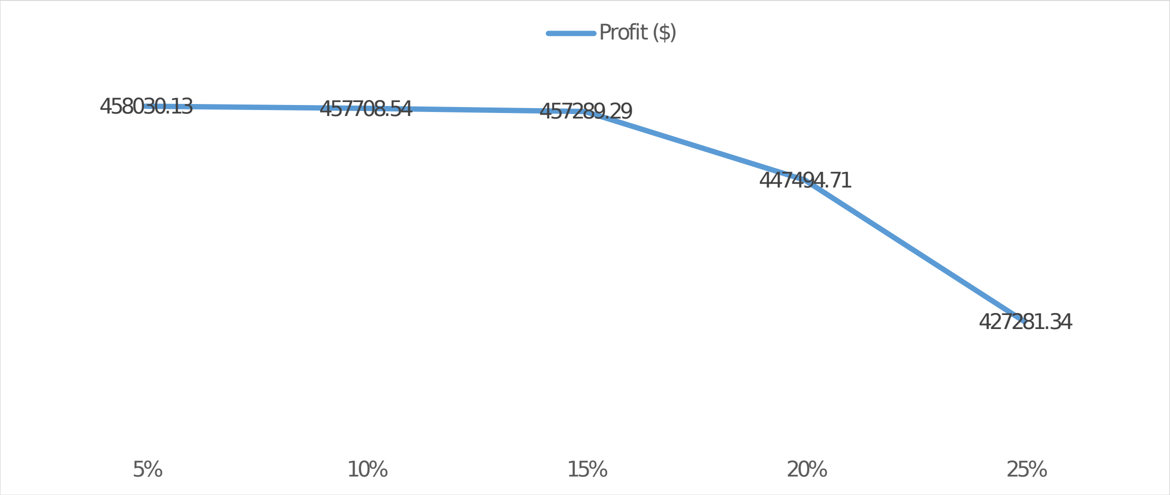


Figure 5: Dairy farm profit variations with respect to changes in individual nitrogen reduction

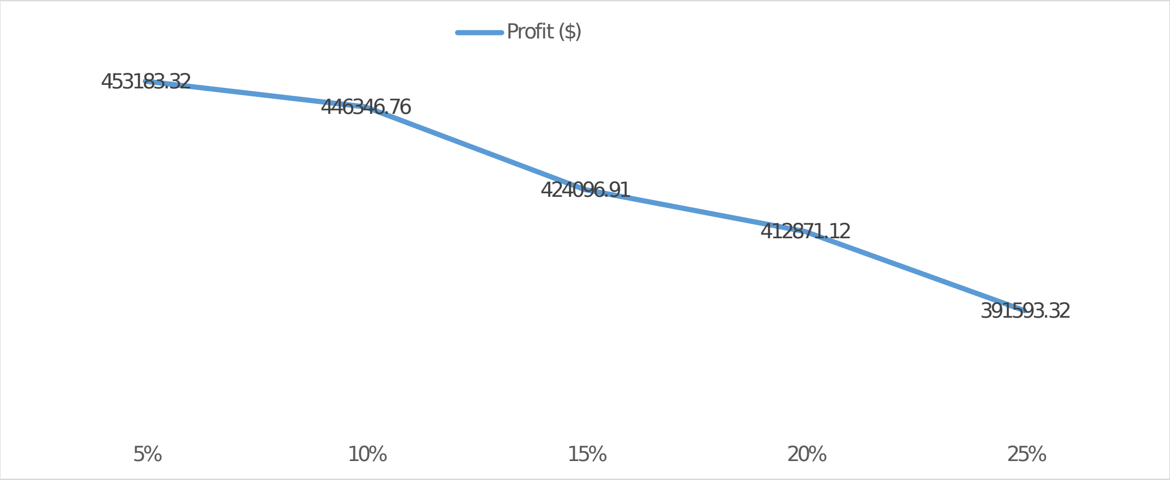


Figure 6: Total farm profit changes under individual phosphorus reduction scenarios

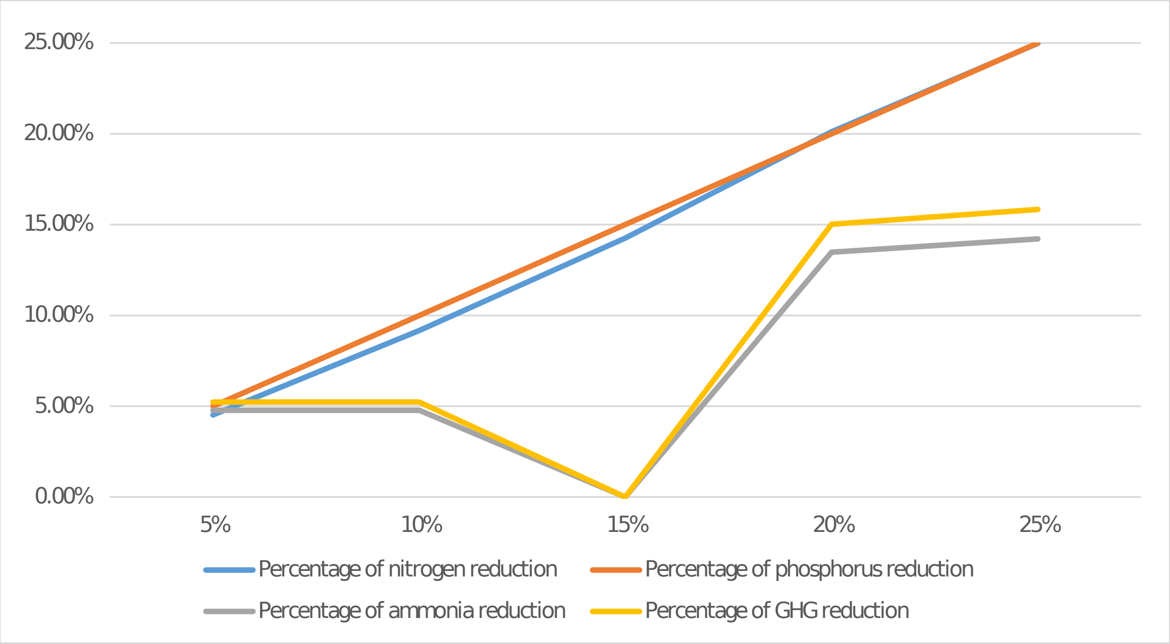


Figure 7: Environmental metrics reduction under individual phosphorus reduction scenarios

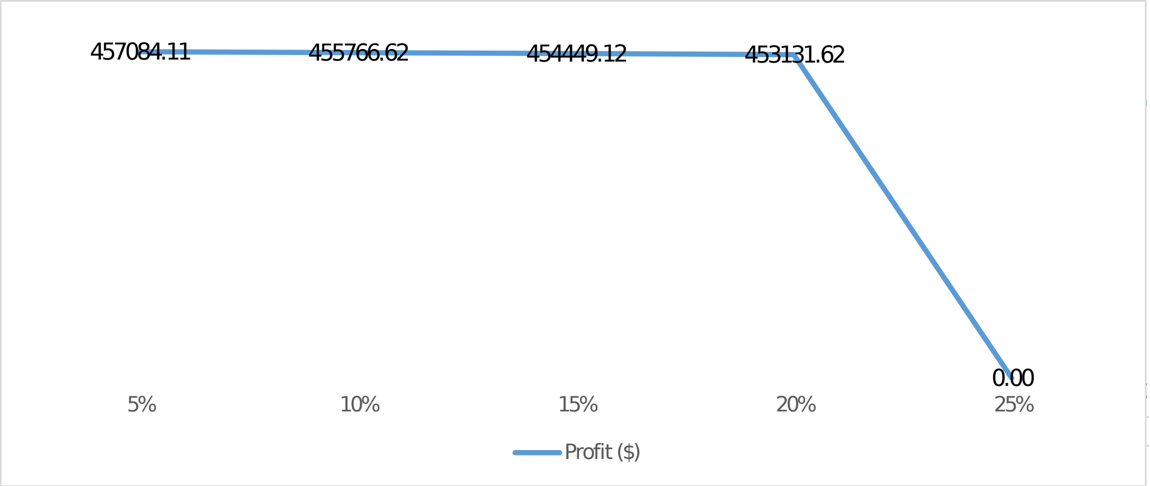
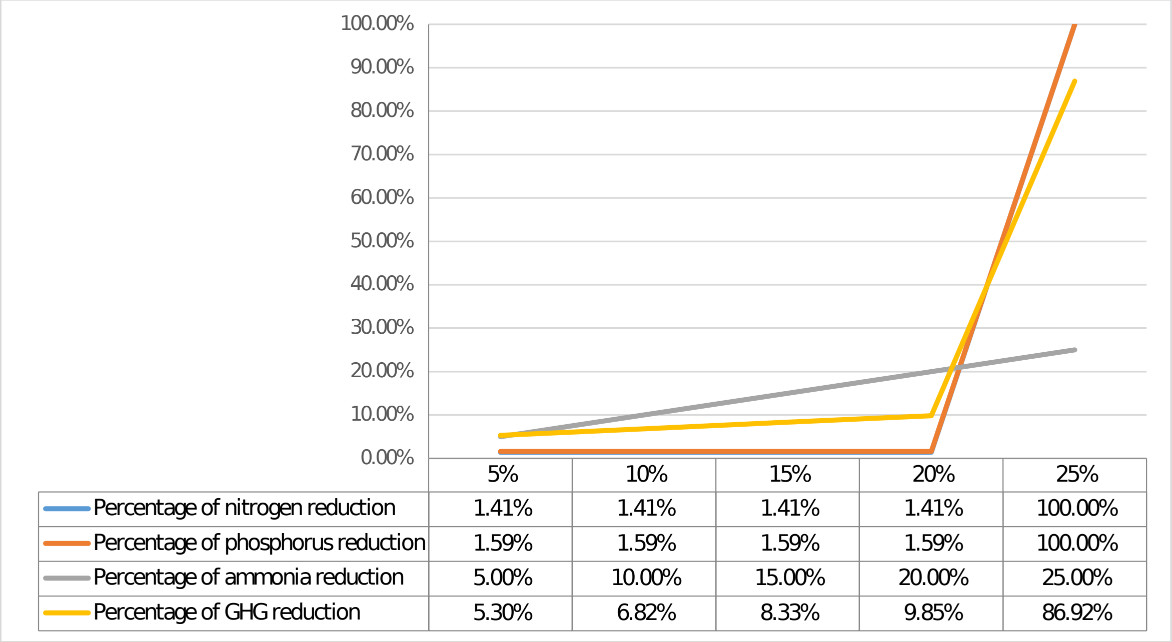


Figure 8: Total farm profit variations with respect to changes in individual ammonia reduction



	5%	10%	15%	20%	25%
Percentage of nitrogen reduction	1.41%	1.41%	1.41%	1.41%	100.00%
Percentage of phosphorus reduction	1.59%	1.59%	1.59%	1.59%	100.00%
Percentage of ammonia reduction	5.00%	10.00%	15.00%	20.00%	25.00%
Percentage of GHG reduction	5.30%	6.82%	8.33%	9.85%	86.92%

Figure 9: Environmental metrics reductions under individual ammonia reduction scenarios

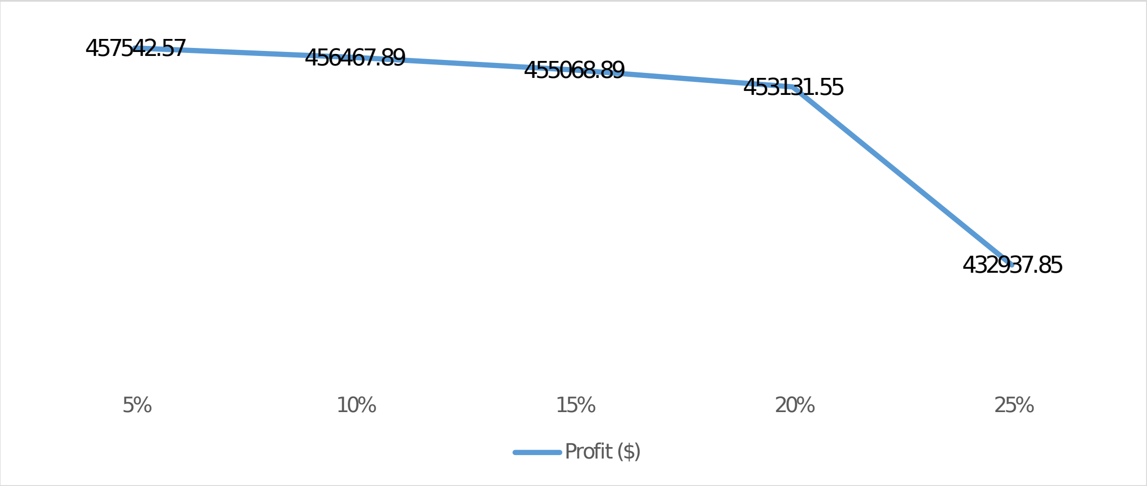
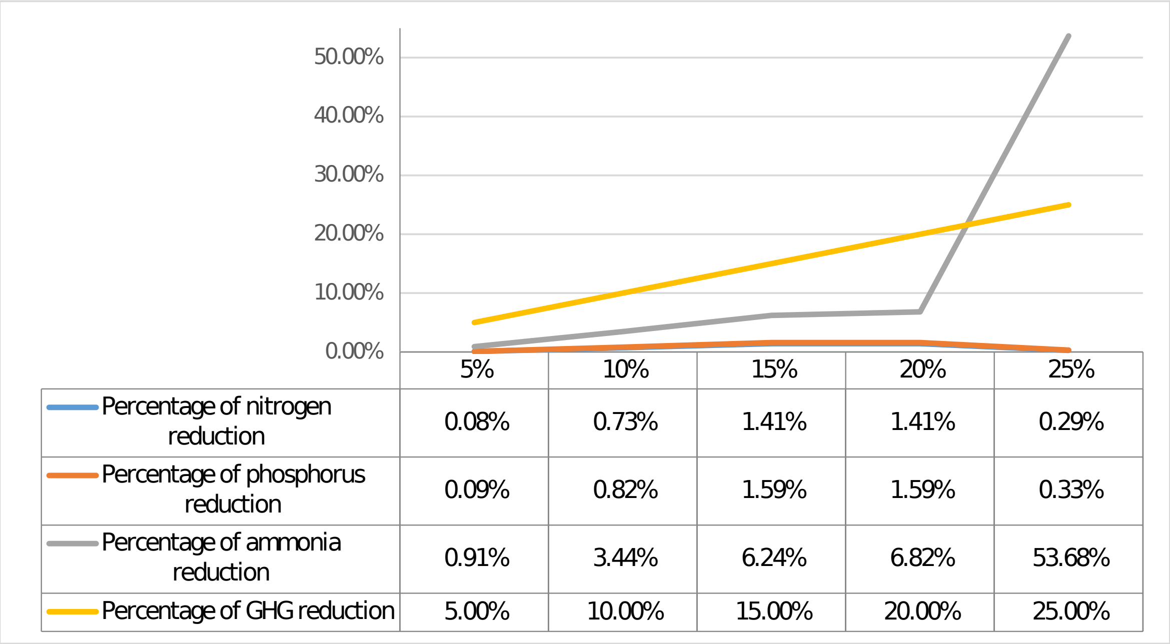
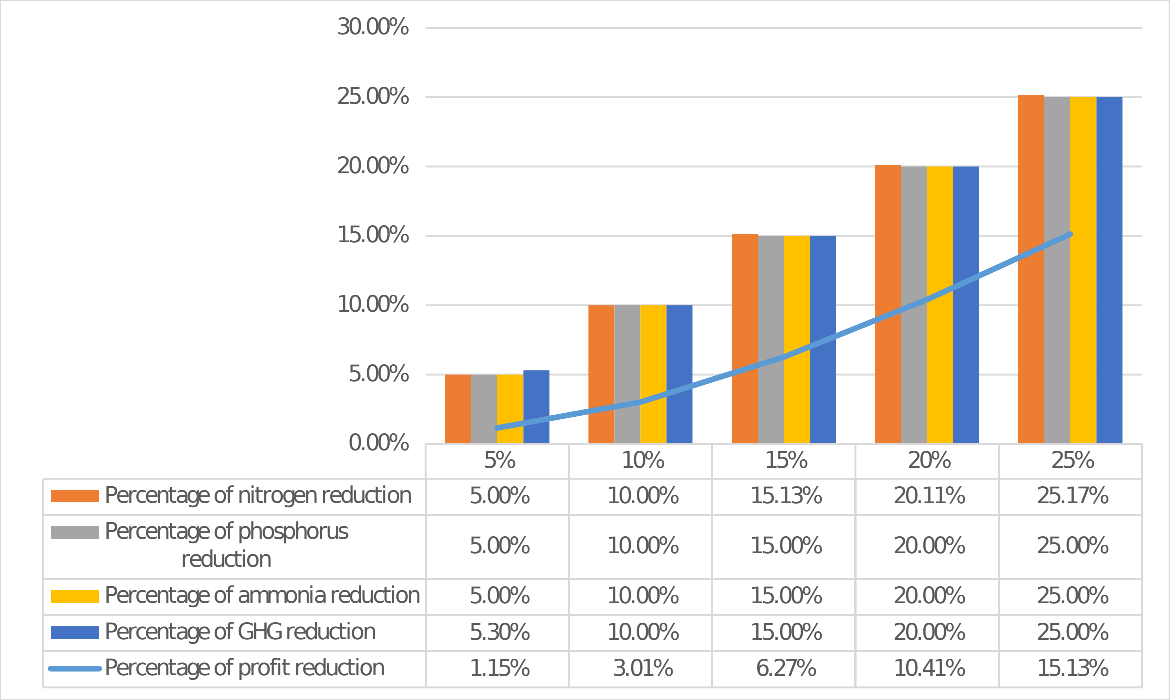


Figure 10: Total farm profit variations with respect to changes in individual GHG reduction



	5%	10%	15%	20%	25%
Percentage of nitrogen reduction	0.08%	0.73%	1.41%	1.41%	0.29%
Percentage of phosphorus reduction	0.09%	0.82%	1.59%	1.59%	0.33%
Percentage of ammonia reduction	0.91%	3.44%	6.24%	6.82%	53.68%
Percentage of GHG reduction	5.00%	10.00%	15.00%	20.00%	25.00%

Figure 11: Environmental metrics reductions under individual GHG reduction scenarios



	5%	10%	15%	20%	25%
Percentage of nitrogen reduction	5.00%	10.00%	15.13%	20.11%	25.17%
Percentage of phosphorus reduction	5.00%	10.00%	15.00%	20.00%	25.00%
Percentage of ammonia reduction	5.00%	10.00%	15.00%	20.00%	25.00%
Percentage of GHG reduction	5.30%	10.00%	15.00%	20.00%	25.00%
Percentage of profit reduction	1.15%	3.01%	6.27%	10.41%	15.13%

Figure 12: Percentage of profit and environmental metrics variation under the incremental reduction of all metrics simultaneously