Estimating Costs of Reducing Environmental Emissions From a Dairy Farm: Multi-objective ϵ-constraint Optimization Versus Single Objective Constrained Optimization

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(ABSTRACT)

Agricultural production is an important source of environmental emissions. While water quality concerns related to animal agriculture have been studied extensively, air quality issues have become an increasing concern. Due to the transfer of nutrients between air, water, and soil, emissions to air can harm water quality. We conduct a multi-objective optimization analysis for a representative dairy farm with two different approaches: nonlinear programming (NLP) and ϵ-constraint optimization to evaluate trade-offs among reduction of multiple pollutants including nitrogen (N), phosphorus (P), greenhouse gas (GHG), and ammonia. We evaluated twenty-six different scenarios in which we define incremental reductions of N, P, ammonia, and GHG from five to 25% relative to a baseline scenario. The farm entails crop production, livestock production (dairy and broiler), and manure management activities. Results from NLP optimization indicate that reducing P and ammonia emissions is relatively more expensive than N and GHG. This result is also confirmed by the ϵ-constraint optimization. However, the latter approach provides limited evidence of trade-offs among reduction of farm pollutants and net returns, while the former approach includes different reduction scenarios that make trade-offs more evident. Results from both approaches indicate changes in crop rotation and land retirement are the best strategies to reduce N and P emissions while cow diet changes involving less forage represents the best strategy to reduce ammonia and GHG emissions.

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(GENERAL AUDIENCE ABSTRACT)

Human activities often damage and deplete the environment. For instance, nutrient pollution into air and water, which mostly comes from agricultural and industrial activities, results in water quality degradation. Thus, mitigating the detrimental impacts of human activities is an important step toward environmental sustainability. Reducing environmental impacts of nutrient pollution from agriculture is a complicated problem, which needs a comprehensive understanding of types of pollution and their reduction strategies. Reduction strategies need to be both feasible and financially viable. Consequently, practices must be carefully selected to allow farmers to maximize their net return while reducing pollution levels to reach a satisfactory level. Thus, this paper conducts a study to evaluate the trade-offs associated with farm net return and reducing the most important pollutants generated by agricultural activities. The results of this study show that reducing N and GHG emissions from a representative dairy farm is less costly than reducing P and ammonia emissions, respectively. In addition, reducing one pollutant may result in reduction of other pollutants. In general, for N and P emissions reduction land retirement and varying crop rotations are the most effective strategies. However, for reducing ammonia and GHG emissions focusing on cow diet changes involving less forage is the most effective strategy.

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Dedication

To my lovely husband, Ghadir

My truest smile and my deepest love

To my parents, Lotfollah Ebadi and Fouzieh Nasiri,

For their unconditional love

To Prof. Darrell J. Bosch

Who always believed in me

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Chapter 1

Introduction

Agriculture is a major source of air and water emissions. For example, the agricultural sector contributes about 48% of the total nutrient loadings in the Chesapeake Bay (Harp, 2018). In addition, the agricultural sector contributed 9% of total U.S. Greenhouse Gas (GHG) emissions in 2017 (USEPA, 2019a). Roughly 60 to 85% of the total U.S. ammonia emission also comes from agricultural sources (Shaver et al., 2014). Although most studies dealing with emissions from animal agriculture have focused on water quality (Gay and Knowlton, 2005), air quality concerns have increased. Air emissions are a concern because they can negatively impact air quality; however, an additional concern is the transfer of nutrients between air and water and the resulting degradation of water quality.

To reduce water and air pollution, the Federal government established the Clean Water Act (CWA) and the Clean Air Act (CAA) in 1972 and 1970, 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% reduction in N loading and a 24% reduction in P loading relative to 2010 levels (USEPA, 2010).

Most of the GHG emitted from agriculture comes from livestock, especially dairy and beef cattle (USEPA, 2016). 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 emissions metrics (White, 2016). Life cycle analysis often focuses solely on GHG emissions (Thoma et al., 2013a) while ignoring possible trade-offs with other environmental impacts including water quality.

Several studies (Tozer and Stokes, 2001, White, 2016, Thoma et al., 2013a,b) emphasize a multi-objective analysis of pollution reduction whereby improving one objective may come at the price of worsening other objectives. Such trade-offs better represent complex environmental impacts. Therefore, a comprehensive analysis of a whole farm system is needed to obtain a better determination of how such emissions and loadings can be controlled cost-effectively.

Agricultural mitigation strategies for crop production defined as Best Management Practices (BMPs) are used to control nutrient runoff on-farm. These practices include buffers, conservation tillage, cover crops, and nutrient management. Dairy production strategies to mitigate pollution include diet optimization. Improving the ability of dairy cattle to efficiently use energy and protein in the diet could potentially reduce GHG emissions without sacrificing profitability (White, 2016). Augmenting the efficiency of an expensive dietary nutrient such as N not only increases the economic competitiveness of the dairy industry but also reduces environmental impacts (Moraes et al., 2018).

Manure handling, storage, and application contribute to GHG and ammonia emissions. About 60% of N inputs into the Bay from Maryland Eastern Shore come from agricultural sources, of which about half are from animal manure (Boesch et al., 2001). Thus, manure management systems can significantly contribute to pollution reduction, especially in the Chesapeake Bay area. While White's (2016) study evaluated the important role of diet management in controlling air pollution, the relative role of manure management in reducing water pollution was not addressed. Yet the choice of manure management system could have important implications for air and water pollution abatement costs.

Understanding how pollution reduction strategies affect farm returns enables us to reduce GHG and ammonia emissions and N and P loadings from dairy production in a cost-effective manner. The objective of this study is to evaluate trade-offs between farm net returns, GHG emissions, N and P loadings, and ammonia emissions on a representative dairy farm. We assume that the farmer is a rational decision-maker who seeks to maximize net returns while reducing environmental emissions.

The scope of this study is the extended farm boundary (Bosch et al., 2008) in which all CO_2-equivalent emissions from feed imports are also considered as a pollution source. 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 products. Pollution associated with these activities is also considered including CO_2 equivalent GHG. Table 1.1 summarizes the sources of each type of pollution on an extended farm.

Table 1.1: Sources of pollution on a farm. Source:(DOE-US, 2007, Feng et al., 2015)

Activity[a]	Methane (CH_4)	Nitrous oxide (N_2O)	Carbon dioxide (CO_2)	Ammonia (NH_3)	N	P
Crop Production	×	×	✓	×	✓	✓
Dairy Production	✓[b]	✓	×	✓	✓	×
Broiler House	×	✓	×	✓	✓	×

a Dairy and broiler production include manure management activities

b Includes enteric fermentation and methane emitted from manure

The representative dairy farm located within Mahantango Watershed in Northumberland County, Pennsylvania is assumed to represent dairy farms in the mid-Atlantic region in terms of optimal responses to water and air quality constraints. We expect that the relationship between reduction in GHG and ammonia emissions, N and P loadings and net returns 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 (net returns 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.

Chapter 2

Literature Review

2.1 Farm Pollution Sources and Solutions

Agriculture is one of the primary sources of nutrient pollution (USEPA, 2019b). Eutrophication- an increase in the rate of supply of organic matter (Nixon, 1995)- is the most important result of nutrient pollution, which degrades water quality. The most severe consequence of eutrophication is hypoxia, which means depletion of dissolved oxygen by the decomposition of organic matter (Boesch et al., 2001). Hypoxia increases as the nutrient inputs into water increase and affects freshwater wildlife by damaging habitat. Hypoxia also reduces the resilience of the Bay ecosystem to eutrophication (Baird and Ulanowicz, 1989).

Animal manure, including that from dairy cattle and broilers, contains significant amounts of primary nutrients especially N and P. The excess amount of manure nutrients applied, beyond the use capacity of crops and holding capacity of soil results in N and P losses by runoff and leaching, which contribute to eutrophication of surface or ground waters. Animal agriculture contributes to water pollution in additional ways such as loss of manure nutrients from milking and feeding areas and manure storage lagoons and holding ponds (Newton et al., 2003).

Atmospheric deposition is an important contributor of N runoff in many regions including the northeast USA. The ammonia volatilized from animal waste is one of the sources of atmospheric deposition (Jaworski et al., 1997), which alters the global N cycle (Vitousek et al., 1997). Atmospheric deposition contributes to eutrophication of coastal and freshwater bodies.

Agricultural N loaded into the Bay decreased about 2% from 2009 to 2017, however, the decrease was mostly due to loss of farmland (Harp, 2018). Among all states located in the Chesapeake Bay watershed, Pennsylvania is the furthest behind in achieving its nutrient loading reduction targets, which is particularly problematic because it has the most agricultural runoff into the Bay (Harp, 2018). Based on the reports of Chesapeake Bay TMDL Tracker (Chesapeake Bay TMDL Tracker, 2017), the total N and P loadings in 2017 from non-regulated agricultural operators of Pennsylvania were about 24.71 and 1.03 thousand metric tons, respectively. These loadings are much higher than those from other sectors such as forests, non-regulated stormwater facilities, and point source pollutants with 9.61, 4.08 and 3.36 thousand metric tons of N loading and 0.18, 0.2, and 0.25 thousand metric tons of P loading, respectively. On the other hand, many studies show that the cost of reducing water pollution in the agricultural sector is less than in any other sector (Stephenson and Shabman, 2017).

Reducing environmental impacts of nutrient pollution from agriculture is a complicated problem that needs a comprehensive understanding of types of pollution and their reduction strategies. To be more precise, we need to explain the pollutants considered in this study in detail.

2.1.1 Nitrogen Loading

Some agricultural practices such as using chemical fertilizers or animal manures can cause pollution of ground and surface waters by N. N loading into the water can be reduced using BMPs such as buffers, conservation tillage, cover crops, and nutrient management. Furthermore, in livestock production, there is a relationship between N intake, milk N and manure N which has been studied extensively and which implies that strategies to regulate N intake through dietary strategies can reduce N loading (Kebreab et al., 2001). Another important factor that affects N loading is manure N management that depends on the effective collection and appropriate field application of manure (Gourley et al., 2012).

2.1.2 Phosphorus loading

Fertilizers and animal manure are primary sources of agricultural P loading (USEPA, 2019c). Research studies show that P contributes to increased eutrophication of surface water through increasing algae growth (Sharpley et al., 1994). P loading can be reduced using previously mentioned BMPs. In a whole-farm study, Spears et al. (2003) found that the relative efficiency of the herd in utilizing P in the diet is the most important factor in reducing P loading in comparison with manure storage and cropping system management.

2.1.3 GHG emission

Increasing GHG emissions by human activities have different environmental effects such as global warming, ocean acidification (Bernstein et al., 2008), smog pollution (West et al., 2006), ozone depletion (Ravishankara et al., 2009) as well as changes to plant growth and nutrition levels (Cleugh et al., 2011, Taub et al., 2008). GHG emission may occur from both livestock and crop production. GHG sources from livestock include enteric fermentation and livestock waste. In addition, for crop production, residue burning, rice cultivation, nutrient applications, and lime application give rise to GHG emissions (DOE-US, 2007). The most significant emissions from livestock operation are methane (CH_4) emission from enteric fermentation, and CH_4 and Nitrous oxide (N_2O) emissions from livestock waste. In addition, crop production and grazing land management can be a source or sink of carbon dioxide (CO_2) (DOE-US, 2007). Thoma et al. (2013b) suggested nutrient management strategies for GHG emission reduction on a dairy farm should connect inorganic fertilizer use and the application of manure for crop production. Tozer and Stokes (2001), also suggest a ration formulation model with multiple objectives including maximization of net returns, and minimization of GHG, ammonia, and N emissions has the potential to reduce nutrient excretion. Lötjönen et al. (2020) construct theoretical and empirical models of a dairy farm under environmental emission constraints and find that water quality instruments provide co-benefits for climate (reduced GHG emissions) and climate instruments provide co-benefits for water quality (reduced N-equivalent emissions).

2.1.4 Ammonia emission

Although ammonia is not a GHG, it may indirectly contribute to agricultural emission of N_2O as well as contributing to N loadings directly after being redeposited on the land. Ammonia is converted to ammonium at varying conversion rates depending on weather conditions. Wu et al. (2008) estimate that the conversion to ammonium happens immediately at a rate of 10 to 40% in summer and 20 to 50% in winter for nearby water sources, or at a considerable distance with a conversion rate of 40 to 100% in summer and 50 to 98% in winter for areas downwind from the emission source. Therefore, ammonia emission can impact quality of the water resources both nearby and distant from the emission sources. Ammonia loss occurs during manure slurry application, housing, slurry storage, and from manure deposited by grazing animals in descending order of importance (Bussink and Oenema, 1998). In addition, Hristov et al. (2011) state that volatilized ammonia from grazing animals and managed manure is deposited on land and eventually converted into N_2O, which contributes about 17% of the N_2O sources in the United States. N_2O has a global warming potential approximately 300 times that of CO_2 (Hristov et al., 2011). Thus, ammonia volatilization from manure can contribute to GHG emissions from agriculture sector (Hristov et al., 2011) as well as the N loading into the water.

2.2 Multiple Objective Programming

Comprehensive multi-pollutant analysis is recommended to address environmental loadings from dairy farms (Tozer and Stokes, 2001, White, 2016, Thoma et al., 2013a,b). In this section, we provide historical and theoretical background for the use of multi-objective programming, the analytical tool of our study, and then construct the conceptual framework of the study with the application of two different methods including multi-objective non-linear optimization and ϵ-constraint optimization.

Multiple objective programming has several conflicting definitions (McCarl and Spreen, 1997). "Multi-objective programming" is assigned to problems with weighted or unweighted multiple objectives, whereas goal programming has been used to refer to multiple objective problems with target levels (McCarl and Spreen, 1997). We can group different multi-objective optimization methods into three broad categories.

2.2.1 First category: No trade-off

The first category includes optimization methods in which a general optimal solution is identified without considering trade-offs among different objectives. The methods in this category use a lexicographic model that is typical of "goal programming models" in which goals are ordered. As McCarl and Spreen (1997) state, in lexicographic programming, once a goal has been dealt with (meeting or failing to meet the target level), its satisfaction remains fixed and the next lower order goal is considered. Consideration of the lower level goals does not alter the satisfaction of higher level goals and cannot damage the higher level goals with respect to target level attainment.

The second approach is to use the genetic algorithm method. The genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems that repeatedly modifies a population of individual solutions to reach a general optimal solution (Alvarez et al., 2004). As Alvarez et al. (2004) state the process begins with a set of randomly selected alternatives (individuals), which are being evaluated based on an evaluation function(s). If the alternatives fulfill the criteria defined by the evaluation function(s) the process is done, otherwise they will be replaced by other alternatives. This process continues until reaching a set of solutions that can not be improved anymore. In addition, as Konak et al. (2006) state there are several approaches for using GA to solve a multi-objective optimization problem including Pareto ranking, weighted average of normalized objectives, and vector evaluated GA (VEGA) in which each sub-population is evaluated with respect to a different objective. Disadvantages of GA methods include "difficulties in non-convex objective functions", and "tending to converge to the extreme of each objective" (Konak et al., 2006).

2.2.2 Second category: Trade-off

The second category involves methods which allow trade-offs among objectives. The simplest method among them is the equally weighted simple multi-objective linear optimization in which the modeler can specify several objectives to be minimized or maximized with respect to environmental and non-environmental constraints (Carvalho et al., 2012). In addition, mixed integer programming (MIP) can be used for some objectives which allow both integer and continuous values for variables. For instance, Gibbons et al. (2005) used a MIP model that maximizes farm net margin (total value of output less variable costs including machinery and labor) by optimizing crop, animal, labor, machinery, storage, housing, and irrigation mix.

A second simple method is using weighted trade-off (with or without targets) modeling in which the objectives can take different weights as well (McCarl and Spreen, 1997). While there are several approaches to specify weights such as decision maker's past actions or survey techniques, still discovering appropriate weights is difficult. The third method is Compromise Programming (CP) (Gebrezgabher et al., 2014). In this method, first, the feasible set that contains the Pareto-efficient solutions for all criteria is identified. Then the subset of Pareto-efficient solutions is identified. Once these efficient solutions are identified, they can be further analyzed using CP to find the best compromise solution. CP defines the best solution as the one in the set of efficient solutions with the smallest distance from an ideal point based on a payoff matrix, which is developed by determining and integrating different economic, social, and environmental criteria.

Although CP can reduce computing time significantly, it has several important disadvantages. First, to conduct a CP the decision maker needs to know the relative preference of the objectives in order to approximate the compromise set for the different decision criteria. Second, as the number of decision-making criteria increases, the efficiency of the CP method decreases. For instance, if the problem involves more than three different attributes then all the potential benefits of CP vanish (Romero and Rehman, 2003).

The other methods under this category are the Augmented and improved Augmented ϵ-constraint methods introduced by Mavrotas (2009) and Mavrotas and Florios (2013), respectively. In the original version of this method, we optimize one of the objective functions using the other objective functions as constraints. By changing the RHS of the constrained objective functions, the efficient solutions can be obtained (Mavrotas, 2009). Although this method demands computational effort, it has several advantages in comparison with the weighting method (Mavrotas, 2009).

1. By using the general weighting method for a linear problem, the result will be a corner solution, which means generating only efficient extreme solutions. But, using the ϵ-constraint method alters the original feasible region and enables the model to produce non-extreme efficient solutions.

2. As stated by Mavrotas (2009) p.457, "the weighting method cannot produce unsupported efficient solutions in multi-objective integer and mixed integer programming problems, while this method does not suffer from this pitfall."

3. The ϵ-constraint method is not sensitive to objectives with different scales, whereas in the weighting method scaling of the objective functions has a strong influence on the obtained results.

4. In weighting method we cannot control the number of generated efficient solutions, however, it is easy to do it through the ϵ-constraint

method by properly adjusting the number of grid points in each one of the objective function ranges.

More details on this method will be discussed later in the third chapter.

2.2.3 Third category: Risk analysis

The last category involves risk methods. Several risk models have been used to evaluate economic and environmental effects of agricultural activities while accounting for the stochastic nature of the environmental impacts. The first method is to use chance-constrained programming, which requires specifying the functional form of the distribution of the environmental variables with significant impacts on the trade-offs and selection of agricultural activities (Qiu et al., 2001). The problem with this method is that the distribution specified for one case may not be applicable for other cases due to site-specific variation in weather and other natural conditions (Qiu et al., 2001).

Another method in this category is Target MOTAD formulation. Teague et al. (1995) used Target MOTAD formulation with some modification to identify farm plans that maximize net return while maintaining environmental risk under a certain level. In order to obtain measures of environmental risk for each production strategy, they used a group of environmental indices such as percolation, runoff of nitrate and pesticides, and differences in toxicity and persistence of pesticides applied on farm for a 20-year period. They argue that representation of risk in this manner allows designing the farm in a way such that it complies with environmental objectives. In addition, they claim that considering environmental risks when assessing income trade-offs shows different results in comparison with deterministic measures. In this study, the model was used to derive a set of environmental risk-return frontiers for the farm. The maximum environmental indices were established based on the optimization without constraints on environmental risk indices. These levels were reduced to 25, 50 and 75% in order to obtain different target levels. Application of the Target MOTAD model requires the decision maker to select a risk level for the expected deviation from an environmental objective, and the scientific basis for selecting a reasonable environmental risk level is weak (Qiu et al., 2001).

Another method for incorporating stochastic environmental risk is using a safety-first constraint. Qiu et al. (2001) argue that with the safety-first constraint the model endogenously determines the environmental risk level after the desired compliance probability with the objective is specified. This method is highly recommended when multiple environmental constraints are considered. The last method in this category is using a multi-objective linear programming model with interval parameters which considers interval coefficients and parameters to solve the general multi-objective model (Han et al., 2011). This method incorporates interval fuzzy linear programming (IFLP) into multi-objective programming and tries to maximize a degree of satisfaction for the fuzzy decision that is constrained by best and least desirable values for each objective function.

The first category of methods that do not consider trade-offs is not appropriate for our study because an objective of our study is understanding the trade-offs between environmental and economic outcomes. Similarly, the last category cannot be helpful for us because our study focuses on a static farm-level analysis. Therefore second category considering trade-offs is appropriate. Non-linear programming with an objective of maximizing net returns subject to constraints on environmental loadings and the ϵ-constraint method will be used because these methods help capture the trade-offs between expected returns and reducing environmental loadings. In the next chapter, we will discuss the empirical model of the study.

Chapter 3

Materials and Methods

As we discussed in the previous chapter, we use two different multi-objective optimization approaches to evaluate the effects on farm net returns of reducing GHG and ammonia emissions and N and P loadings: *a*) optimization of a single objective (farm net returns) while including environmental objectives as constraints, and *b*) optimization using augmented ϵ-constraint optimization (Figure 3.1). In each case, the mathematical model selects among different crops subject to land, machinery, rotation, manure spreading, crop and cow nutrient requirements, and other constraints.

For crop production, we include cover crops, nutrient management, buffers, reduced tillage, and idling land in the Conservation Reserve Program (CRP) as strategies to reduce N and P loadings. In dairy production, the model selects among different feed options subject to nutrient and maximum dry matter intake (MDI) requirements, which are specified by cow grouping (the number in population, time in sys-

Figure 3.1: Farm-level optimization model

tem). Based on a previous study by Feng et al. (2015), we consider diet optimization as a strategy to reduce environmental emissions with the focus on N and P requirements for dairy cattle. Finally, for manure management, the model estimates the manure produced by the dairy cattle and broiler house. Manure is assumed to be handled with slurry lagoon and solid storage as two components of an overall system. The GHG and ammonia emissions and N and P loadings from the manure management system are estimated.

Tozer and Stokes (2001) suggest that expected trade-off between N and P loading reduction is a competing relationship. They also argue that the N loading reduction has a competing relationship with cost, but P loading reduction does not relate to cost as strongly as N. This result was mainly due to different nutrient valuation in the objective function. In particular, Tozer and Stokes (2001) defined the N objective function as a function of fecal and urinary protein and P objective function as a function of P intake. Thus, the difference in the costs of reducing N and P loadings comes from the difference in N and P input costs. There is less information about trade-offs of N and P loadings with GHG and ammonia. 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 3.2 with a competitive relationship between points *a* and *b*.

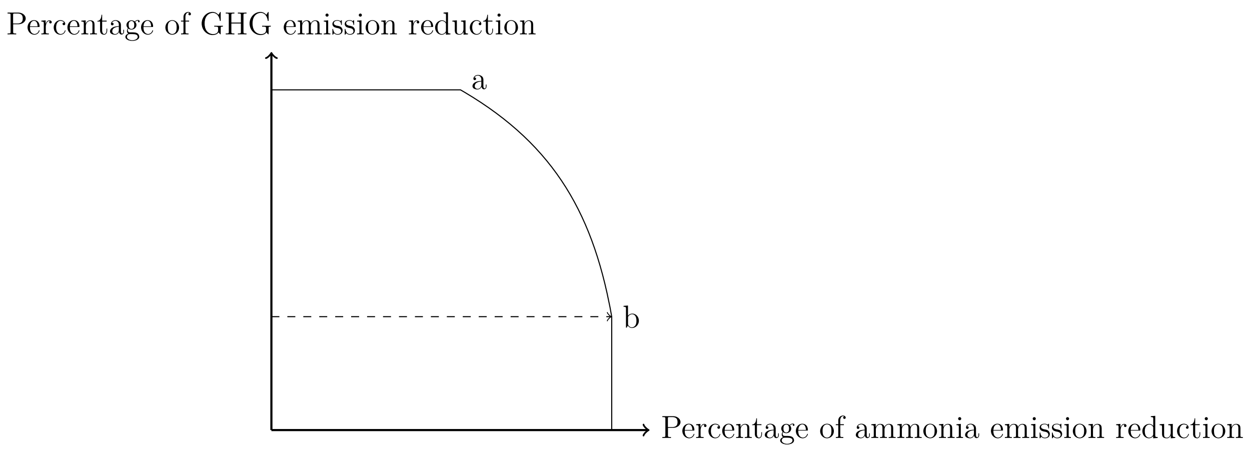

Figure 3.2: Expected trade-off between the percentage of GHG and ammonia emission reduction

3.1 Non-linear Programming

The first multiple objective programming approach is non-linear programming (NLP) due to several non-linear constraints. NLP maximizes total farm net returns while considering environmental objectives as constraints. The baseline scenario maximizes total farm (crop, livestock, and manure management) net returns without any constraint on environmental emissions. This optimization approach consists of individual and jointly incremental reductions of environmental emissions.

3.2 ϵ-Constraint Optimization

The original version of the ϵ-constraint method optimizes one of the objective functions while using the other objective functions as constraints. By changing the RHS of the constrained objective functions, efficient solutions can be obtained (Mavrotas, 2009). Here we use the Augmented ϵ-constraint methods proposed by Mavrotas (2009). Although this method demands computational effort, it is advantageous in certain ways in comparison with the weighting method (Mavrotas, 2009). Advantages include: producing non-extreme efficient solutions, insensitivity to objective functions with different scales, and the ability to manage a large number of efficient solutions.

Assume the following multi-objective mathematical model:

$$\begin{aligned} Max \quad & (f_1(x), f_2(x), ..., f_n(x)) \\ s.t. \quad & x \in S, \end{aligned} \tag{3.1}$$

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):

$$\begin{aligned} & Max \quad (f_1(x)) \\ st \quad f_2(x) \geq e_2, \;\; f_3(x) \geq e_3, \;\; \ldots \;\; & f_n(x) \geq e_n, \;\; x \in S, \end{aligned} \tag{3.2}$$

where e_i is the RHS of the constrained objective functions.

To apply the ϵ-constraint method, we need the range of $n-1$ objective functions to be employed as constraints. A common approach to determine these ranges is through a payoff table which includes the results obtained by 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 determining the pay-off table, we divide these ranges into nine equal intervals, then, we use these ten grid points as the values of each e. If all $n-1$ objective functions used as constraints are binding we have an efficient solution, otherwise, the result is a weakly efficient solution (Mavrotas, 2009). To avoid generating weakly efficient solutions, Mavrotas (2009) proposes the following transformation for the objective function constraints to require the model to produce only efficient solutions.

$$\begin{aligned} Max \quad (f_1(x) + \epsilon \times (s_2 + s_3 + ... + s_n)) \\ st \quad f_2(x) - s_2 = e_2, \\ f_3(x) - s_3 = e_3, \\ \vdots \\ f_n(x) - s_n = e_n, \\ x \in S, \;\; and \;\; s_i \in \mathbb{R}^+ \end{aligned} \tag{3.3}$$

where ϵ is an adequately small number (usually between 10^{-3} and 10^{-6}) and s_i are the slack or surplus variables for the ϵ-constraints. Moreover, to avoid any scaling problems related to s_i , Mavrotas (2009) suggests dividing the s_i terms by r_i, where r_i is the range of the $i-th$ objective function, which is calculated from the pay-off table.

$$
\begin{aligned}
Max \quad (f_1(x) + \epsilon \times (\frac{s_2}{r_2} + \frac{s_3}{r_3} + ... + \frac{s_n}{r_n})) \\
st \quad f_2(x) - s_2 = e_2, \\
f_3(x) - s_3 = e_3, \\
\vdots \\
f_n(x) - s_n = e_n, \\
x \in S, and \;\; s_i \in \mathbb{R}^+
\end{aligned}
\tag{3.4}
$$

In this study, the first objective is maximizing farm net returns, which includes net returns from crop production and sales, livestock production, and manure sales, minus costs of crop and 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 3.1 and Table 3.2, respectively. Table 3.1 and Table 3.3 represent the list of parameters and variables used in Equation 3.5, respectively. The mathematical equation takes the form of:

$$\begin{aligned} f_1 = -\sum_f x(f) * TC(f) - \sum_f Prc(f) * BPR(f) + \sum_f Sld(f) * SPR(f) \\ + x(broiler) * NRL + \sum_u S(u) * MSP(u) - \sum_u A(u) * MAC(u) \\ - \sum_n C(n) * NPR(n) + Tmilk * MPR - \sum_c x(c) * FC \\ + \sum_c x(c) * GR - TBMPC \end{aligned} \tag{3.5}$$

Table 3.1: Parameters of the model

Parameter	Units (in 2018$)	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
FC	$ per cow	Fixed cost
GR	$ per cow	Gross revenue excluding milk revenue
MPR	$ per kg	Price of milk

Table 3.2: Definition and elements of sets and subsets in the model equations

Set	Set name	Elements	Element definitions
f	Feeds	See Table 3.4	Includes on-farm and off-farm feeds
n	Nutrients	P, Ca, MP, ME, N, K	Phosphorus, calcium, metabolized protein, metabolized energy, nitrogen, and potassium
a	Animals	c1, ..., c5,Broiler	One to 5 years old cows and broiler house
b	BMPs	subsets: TILL,CC,NM,BUF	Details are provided in Table 3.5
rt	Rotation	subsets: with/out cover crops	Crop rotation
m	Months	1,...,12	Months (January=1)

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

Table 3.3: Variables of the model

Variable	Definition
$x(f)$	Hectares of crops produced
$Prc(f)$	Kg of feeds purchased
$Sld(f)$	Kg of each on-farm feed sold
$x(broiler)$	Number of 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
$x(c)$	Number of cows in each category
$TBMPC$	Total BMP costs (see Equation 3.10)

farm.

$$f_2 = GHG(B) - TGHG \tag{3.6}$$

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:

$$f_3 = Am(B) - TAm \tag{3.7}$$

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, where total N loadings include N loading from crop production, N loading from ammonia deposition, and N loss from nitrous-oxide leaching. N loading reductions can be achieved by substituting less polluting crops or by reducing livestock numbers or by exporting manure or by making dietary changes for cows. The N reduction objective function takes the form of:

$$f_4 = TN(B) - TN \tag{3.8}$$

Where

$TN(B)$: Total N loading without any environmental constraints (Baseline scenario)

TN: Total N loaded under the constrained scenario

The last objective function minimizes the total P loading from crop production. Similar to the N loading, P loading reductions can also be achieved by substituting less polluting crops or by reducing livestock numbers or by exporting manure. The P loading reduction objective function takes the form of:

$$f_5 = TP(B) - TP \tag{3.9}$$

Where

$TP(B)$: Total P loading without any environmental constraints (Baseline scenario)

TP: Total P loaded under the constrained scenario

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

3.3 Study Area

The study is carried out in the WE-38, a 7.3 km2 sub-watershed of Mahantango Watershed, located in Northumberland County, Pennsylvania (Bryant et al., 2011). We use the data on crop yields and crop N and P loading generated by SWAT-VSA (Easton et al., 2008, Collick et al., 2015, Wagena et al., 2018, Bosch et al., 2018, Xu et al., 2019). The model will be run using the Generic Algebraic Modeling System (GAMS; https://www.gams.com/). The model simulates a one-year time frame.

3.4 Farm Model

We divide the activities within the dairy farm into three main activity groups including crop production, livestock (dairy and broiler) production, and manure management.

3.4.1 Crop Production

The model selects among alternative crops subject to land, machinery, crop rotation, BMP, and animal feed requirements. Total land available for crop production and pasture is 400 and 23 hectares, respectively. Crop characteristics are shown in Table 3.4. Crops referred to here as feeds are dimensioned on the type of crop, rotation, and BMPs employed in the production of that feed (Table 3.2 and Table 3.5). Crops produced on farm can be both sold and purchased, however, the purchase price is assumed to be 10% more than the 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. Land and fertilizer costs are not included in Table 3.4. Fertilizer costs are directly considered in the farm net returns calculations (Equation 3.5). All costs and revenues are expressed in 2018$.

Table 3.4: On-farm crops

Crops	Cost[a] ($/ha)	Yield(mt/ha)[b]	Price ($/kg)	N loading (kg/ha)	P loading (kg/ha)	GHG emission (kg/kg)[c]
Corn grain	884.36	8.26	0.24	36.93	18.46	0.39
Corn silage	1342.06	47.22	0.08	36.93	18.46	0.09
Soybean	452.85	1.89	0.70	28.40	14.20	0.42
Double-cropped Soy[d]	38.22	1.13	0.70	14.20	7.1	0.42
Wheat	418.51	5.51	0.26	56.92	28.46	0.69
Alfalfa[e]	708.91	8.99	0.19	1.71	2.59	0.44
Pasture	56.24	1[f]	0.11[g]	25.09	12.46	0.28

a Curran and Lingenfelter (2015)
b Crop yields and N and P loadings as estimated by SWAT-VSA
c USDA/ERS (2013)
d "Double-cropped soybean yield is 60% of full-season soybean based on July 10 planting date" (Curran and Lingenfelter, 2015)
e Alfalfa silage yield is obtained by multiplying hay yield times 2.43 the ratio of hay dry matter (85%) to haylage dry matter (35%) (Bosch et al., 2018)
f Dry hay equivalent.
g Based on the selling price for purchased grass forage Horner and Sexten (2018)

Crop BMPs are used to reduce nutrient loading into surface and ground-water. Nutrients come from different sources including manure production, fertilizer application, and ammonia deposition on land. The total annual cost, as well as the effectiveness of these BMPs, are presented in Table 3.5. CRP (Conservation reserve) cost is estimated as "annual average cost for introduced species and native species amortized over five years" which is \$140.35 per hectare (NRCS, 2019b). The CRP Regular Rental rate (revenue) is \$230 per hectare (USDA-FSA, 2018). CRP is assumed to result in 100% reduction in N and P (up to 100 ha of land). Based on Maryland enterprise budgets (Beale et al., 2019), conservation tillage (no-tillage planting) costs are negative reflecting that no-till has higher net returns than conventional tillage. Nutrient management has two types: with manure and without manure. Nutrient management with manure is more effective than nutrient management without manure in N and P loadings reduction. Nutrient management costs include designing the nutrient management plan and implementation of the plan. Cover crop options include none, rye cover, and cover crop with commodity wheat. Cover crop costs include seed, chemical, labor, and machinery costs of planting the cover crop commodity. Crop buffer costs include land preparation, seeding, and maintenance for grass buffers. The opportunity cost of land removed from crop production is not included in Table 3.5, however it is included in the farm net returns calculations (Equation 3.5). Pasture buffer include annualized costs of establishing on off-stream water source for pastured animals including pipelines, tanks, and pumps.

Table 3.5: Costs per hectare (2018$) of BMPs and BMP effectiveness

BMP name	Description	Total annual cost ($ per ha)	N reduction (%)[a]	P reduction[a] (%)
No-till planting	High residue planting. Minimum of 60% crop residue at planting.	-135.34 [b] (Beale et al., 2019)	12	11
Crop buffers[c]	30 meters wide linear strip of permanent grass buffer bordering streams	91.86 (Chesapeake Bay Program, 2019b)	13	22.5
Pasture buffers [d]	Off stream watering without fencing serving 20 hectares pasture.	85.25 (Chesapeake Bay Program, 2019b)	5	8
Cover-crop normal	Rye cover planted during normal planting window (two weeks prior to average first frost date)	188.66 (Chesapeake Bay Program, 2019b)	27	0
Cover-crop commodity wheat	Winter wheat with no fall nutrients applied. Planted two weeks prior to average frost date	1121.29[e] (Beale et al., 2019)	10	0
Nutrient management with manure	Adjust timing, placement, and amp; rate of nutrient applications	58.4 (Chesapeake Bay Program, 2019b)	27.3	42.4
Nutrient management without manure	Adjust timing, placement, and amp; rate of nutrient applications	58.4 (Chesapeake Bay Program, 2019b)	12.5	15.4
Conservation reserve	Annual average cost for introduced species and native species amortized over five years	140.35 (USDA-FSA, 2018)	100	100

a Chesapeake Bay Program (2019a)

b The cost is considered negative because it is more profitable per hectare than conventional tillage.

c Reduction applies to the upslope area equal to four times the grass buffer area.

d Reduction applies to all of the pasture areas.

e Includes costs of planting wheat and soybean in a double crop rotation.

The selected BMPs are the most cost-effective ones for the Chesapeake Bay (Simpson and Weammert, 2009, Chesapeake Bay Program, 2019, Chesapeake Bay Foundation, 2015). Total BMP cost is calculated based on the summation of costs of all BMPs used to grow all crops:

$$\sum_{b}\sum_{rt}\sum_{f}(x(rt,f,TILL,CC,NM,BUF)*BMPcost(TILL,BUF,CC,NM)) \tag{3.10}$$

where,

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

Conservation practices including nutrient management plans, cover crops, continuous no-till, and off-stream watering are efficiency BMPs that reduce loadings where they are applied. Stream buffers result in nutrient loading reductions from area converted to grass buffers as well as the up-slope area that drains through the buffer (Van Houtven et al., 2012). Cover crop planting is limited to 372 hectares by machinery and labor constraints (Bosch et al., 2018). The maximum land available for stream buffers is based on stream frontage. A 30-meter wide buffer can be planted on either side of a stream that passes through agricultural land. Grass buffer can treat an area equal to four times the area planted in grass buffer (Van Houtven et al., 2012). Total hectares of land that could be retired through the Conservation Reserve Program

(CRP) should be at most 25% of the total land available (NSAC, 2019).

Crop rotations considered in the model include continuous corn, corn-soybeans, two years corn-three years alfalfa, one-year corn-two years alfalfa, one-year corn followed by double-cropped wheat and soybeans, continuous grass pasture, and rye cover following corn or soybeans. Corn may be produced as grain or silage. Moreover, corn grown in rotation with soybean, two years alfalfa, and three years alfalfa has an increased yield of 4, 8, and 11%, 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 and commercial fertilizer applications (Curran and Lingenfelter, 2015), and ammonia deposition. Legume N carryover is 16.667 kg N per mt yield for soybean based on Curran and Lingenfelter (2015) calculations. An average of 31% of the total ammonia emission will be deposited on land (Loubet et al., 2009). As Loubet et al. (2009) state 37.5% of the total ammonia deposited on land will be delivered to surface waters as N. Remaining 62.5% of the total ammonia deposited on land will be available to crops as source of N. The unit prices for each commercial fertilizer used including application are $1.64, 1.93, and 1.07 per kg of N, P, and potassium (K), respectively.

3.4.2 Livestock Production

Animal diet optimization is one method that helps to improve farm net returns, however, its potential environmental benefits have not been investigated well (White, 2016). As stated by McCubbin et al. (2002) excess dietary N excreted as manure may contribute to N 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 the environmental impacts of dairy production.

We optimize the amount of feed required by each category of dairy cows. There are five categories including one, and two-year-old heifers, and three, four, and five year and older cows. The decision variable is the number of cows kept which is dimensioned on the age of the cows in any month. The number of cows is allowed to vary by cohort. The cow's population is calculated based on culling rate and the farm maximum capacity for dairy cows, which 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 P, calcium (CA), metabolized energy (ME) and metabolized protein (MP) as the basic diet requirements. The nutrient requirements for cows were calculated based on National Research Council, Board on Agriculture and Natural Resources, Committee on Animal Nutrition, Subcommittee on Dairy Cattle Nutrition (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 is required to consist of 40 to 60% forages. In addition, there is a Maximum Dry Matter Intake (maxDM) level for each cow based on their age (National Research Council, Board on Agriculture and Natural Resources, Committee on Animal Nutrition, Subcommittee on Dairy Cattle Nutrition, 2001).

Total milk production is a function of the population of cows lactating in each month times average milk yield per cow. Therefore, average milk production varies by cohort every month. According to APHIS (2009), the national average milk yield per cow is 10,219 kg/305 days. We assumed a similar average milk yield of 11,922 kg/305 days for each lactating cohort (c_3, c_4, and c_5) as suggested by White (2016). Gross revenue (excluding milk revenue) for dairy production is $1,375 per head in 2018 U.S. dollars (Eberly and Groover, 2011). Milk revenue is assumed to be $0.34 per Kg based on Eberly and Groover (2011). For consistency both milk price as well as costs were taken from Eberly and Groover (2011) and expressed in 2018$. The $0.34 per kg price compares with the average milk price of $0.33 in Pennsylvania in 2018 (USDA/ERS, 2018). Total variable cost is internal to the model and includes cost of purchased feed. Total diet cost for cows consists of the cost of purchasing off-farm feeds and raising farm-produced feeds. Total fixed cost for dairy production is $2,486 per head based on Eberly and Groover (2011). Accordingly, the profitability of dairy production depends on milk production and diet cost.

The broiler house has the capacity of 242,000 birds per year. The total gross revenue (excluding broiler litter sales) and the total variable costs are $67,628 and $16,095 per house, respectively (Rhodes et al., 2011) in 2018$. This gives a total net revenue of $51,533 dollars per house per year. The farm has a maximum of one broiler house. Feed for broilers is supplied by the poultry integrator.

3.4.3 Manure Management

Dairy and poultry manure nutrients can be recycled through crop production especially when multi-cropping systems are utilized (Newton et al., 2003). Manure collection, storage (liquid and solid), and application practices depend on how dairy cattle are housed and vary with farm size (Gourley et al., 2012). Almost half (49.4%) of the U.S. dairy operations with liquid manure use slurry lagoons as their first treatment strategy (USDA-NAHMS, 2007). We assume slurry lagoon as the manure management strategy for liquid manure. In addition, there is solid storage for solid manure production.

Manure management is comprised of manure production, storage, spreading, and selling. Dairy cows produce 21.1 thousand liters of liquid manure and 8.4125 mt solid manure per head, annually (Bosch et al., 2018). Also, including manure excretion and litter bedding, a broiler house produces 376 mt litter annually (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 \$15.22 per mt (in 2018 dollars) (Pease et al., 2012), while dairy solids can be given away and dairy liquid can be given away if the exporting farm pays the spreading costs. Dairy solid and litter can be spread at the costs of \$6.69 per mt while dairy liquid spreading costs are \$1.90 per 1000 liters (Van Kooten et al., 1997).

3.4.4 Environmental Calculations

Nutrient management in livestock production protects air quality by reducing N emissions such as ammonia and oxides of N. Based on the N mass balance (Stephenson et al., 2013) prior to manure field application the primary source of N loss is air emissions. N can be emitted primarily as ammonia (NH_3) or as nitrous oxide (N_2O) at this stage. In addition, a decrease in ammonia loss may increase nitrate leaching and denitrification (Bussink and Oenema, 1998). To prevent an increase in nitrate leaching 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-NRCS, 1992), we estimated the ammonia emissions using USEPA (2004) emission factors for the flush dairy barn and broiler house. 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 3.3. Details on ammonia emission calculations as well as other environmental emissions and loading are discussed in Appendix A.

GHG emissions are divided into 4 different categories including nitrous oxide (N_2O), enteric methane, manure methane, and carbon dioxide (CO_2) emissions from crop production. GHG emissions are expressed as CO_2-equivalents. Tier 2 methods of IPCC (2006) have been used for N_2O emissions. N_2O emissions include all direct, leached, and volatilized emissions (see Appendix A, Equation A.2). In general, N_2O has direct and indirect emission pathways. Direct emissions are based on a fraction of total N excretion. The indirect emissions include volatilisation meaning N_2O emissions from "atmospheric deposition of N volatilised from managed soil" and leaching meaning N_2O emissions from "leaching and runoff" (IPCC, 2006). As White (2016) recommends, we use Moe and Tyrrell (1979) equations to calculate enteric methane emissions. Enteric methane is calculated based on the DMI (dry matter intake) and particular feed content such as nonstructural carbohydrates, hemicellulose, and cellulose (see Equation A.5). Manure methane emissions are calculated based on volatile solid excretion (IPCC, 2006) (see Equation A.6). The GHG emissions from crop production include (CO_2) and N_2O emissions for on-farm crop production as well as GHG emissions from transporting off-farm feeds (White, 2016) (see Equation A.8). The sources of GHG calculations are USDA/ERS (2013) and Burek et al. (2014). N and P 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 suggested by previous studies (Bosch et al., 2018, Easton et al., 2008, Collick et al., 2015).

3.5 Multi-Objective Optimization

3.5.1 NLP Optimization

In the baseline scenario, we maximize farm total (crop, livestock, and manure management) net returns without any constraint on environmental impacts. Non-linearity of the model is a result of non-linear equations that address environmental calculations for N_2O, enteric methane, and manure methane (see Appendix A). The equations are nonlinear because of the multiplication of the cow population variable by the DMI variable (Equation A.5) and N excretion and volatile solids excretion (Equation A.2 and Equation A.6). In addition, we consider twenty-five individual and five joint reduction scenarios. The Chesapeake Bay TMDL imposes 25 and 24% reduction in N and P loading, respectively, relative to 2020 loads (USEPA, 2010). To the best of our knowledge, there is no emission reduction imposed regarding air pollution, thus we defined the maximum level of 25% reduction for all pollutants. The 25 individual reduction scenarios correspond to 5, 10, 15, 20, and 25%

reduction of N, P, ammonia, and GHG, respectively. The five joint reduction scenarios correspond to 5, 10, 15, 20, and 25% reductions in N, P, ammonia, and GHG at the same time.

3.5.2 ϵ-constraint Multi-objective Optimization

The ϵ-constraint model optimizes one objective function subject to constraints on other objectives with multiple right-hand sides (RHS). In our case there are $K = 5$ objective functions corresponding to, "net returns", "N", "P", "ammonia", and "GHG". Net returns are maximized while N, P, ammonia, and GHG emissions are minimized. The right-hand sides for the constrained objectives are determined from the payoff table generated by the single optimization of each objective (Table 3.6). For instance, by maximizing the total farm net returns the value for each objective function will be $507,909 for the total farm net return, with loadings of 13,880 kg of N, 175 kg of P, 14,382 kg of ammonia, and 3,315,813 kg of GHG. Minimum values for N, P, ammonia, and GHG are zeros. All other model inputs including environmental calculations and limitations on farm production are the same as for the NLP optimization.

Table 3.6: Payoff table generated by ϵ-constrained optimization

	Farm net returns ($)	N level (kg)	P level (kg)	Ammonia level (kg)	GHG level (kg)
Max farm net returns	507,909	13,880	175	14,382	3,315,813
Min N emission	0	0	0	0	0
Min P emission	0	0	0	0	0
Min ammonia emission	0	0	0	0	0
Min GHG emission	0	0	0	0	0

To avoid weakly efficient solutions we develop the augmented objective function as shown in Equation 3.11.

$$f = Z(NR) + \epsilon * (\sum_{k \neq NR} \frac{S_k}{r_k}) \tag{3.11}$$

where,

f: Auxiliary variable for the objective function

K: Objective functions including, "net returns", "nitrogen", "phosphorus", "ammonia", and "GHG"

$Z(k)$: The objective function variable

ϵ: Small number (10^{-3})

$S(k)$: Slack/surplus variables for the ϵ-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 3.12.

$$Z(k \neq NR) - S(k) = RHS(k \neq NR) \tag{3.12}$$

where,

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

In the next step, we generate the payoff table (Table 3.6) by the application of lexicographic optimization. For example, the minimum N emission row means N level is 0 as are all other variables. The same happens when P, ammonia, and GHG emissions are minimized. Afterward, we define a set of grid points (Table 3.7) using a payoff table, to produce efficient solutions. In our case, we defined 10 grid points by simply dividing the ranges specified by the payoff table into 9 equal intervals. Then, we allow the model to walk through the grid points by using a loop to optimize the objective function f. For instance, for minimizing objective functions, the loop starts from the maximum and gradually decreases the RHS of the respective constraint up to the point where the corresponding objective equals zero. Then, the algorithm exits and proceeds with the next grid point from the previous objective function. For instance, for minimizing objective functions (N, P, ammonia, and GHG) the process starts from the maximum and gradually decreases the RHS of the respective constraint. Starting with N, the process reduces the allowable N as shown in Table 3.7. When the RHS of the N minimizing objective function becomes zero the algorithm exits the loop and the process continues with the next environmental constraint. This process continues until the minimum feasible grid point of zero has been evaluated for each environmental constraint. Then the Pareto optimal solution is chosen as the final solution for the problem.

Table 3.7: 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}
N	1,383	2,766	4,149	5,532	6,915	8,298	9,681	11,064	12,448	13,831
P	17	35	52	69	86	104	121	138	156	173
Ammonia	1,438	2,876	4,315	5,753	7,191	8,629	10,067	11,505	12,944	14,382
GHG	298,531	597,062	895,593	1,194,125	1,492,656	1,791,187	2,089,718	2,388,249	2,686,780	2,985,312

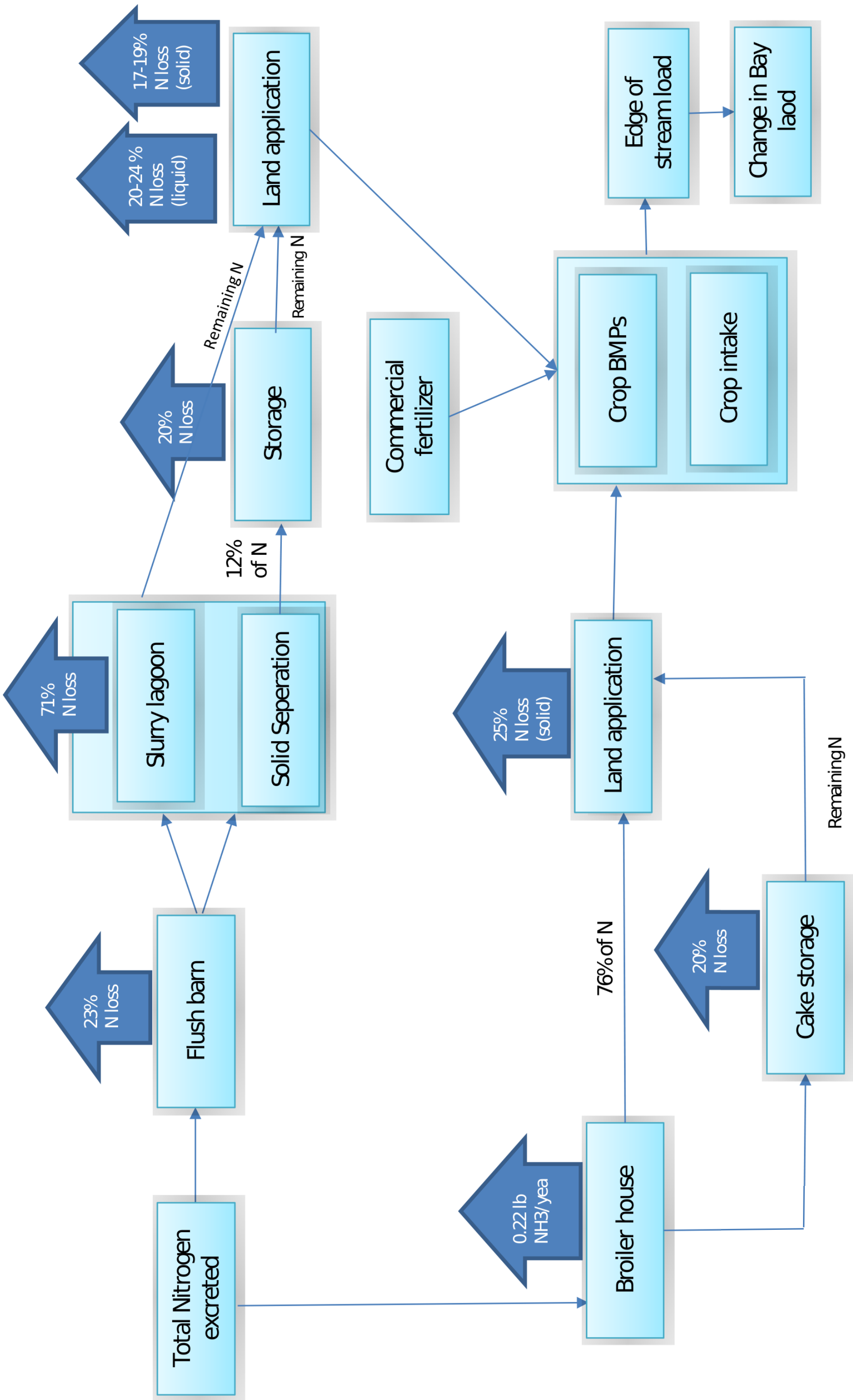

Figure 3.3: Total farm ammonia emissions (USEPA, 2004)

Chapter 4

Results and Discussion

4.1 Analysis of the NLP Optimization

4.1.1 Evaluating Baseline Performance

The environmental output of the baseline scenario for the total production system along with the literature averages are shown in Table 4.1. Total GHG emissions by crop and livestock production are 1,502,651, and 1,816,419 kg of CO_2, respectively. Total ammonia production is 14,381 kg of which 31% is deposited on land, and 11.6% is loaded into surface water as N with a conversion rate of 0.82 from ammonia to N (NRCS, 2019a). Total N excreted from the dairy cows and broiler house are 11,833 and 12,408 kg, respectively. Total N and P loadings are 13,880 and 175 kg, respectively. N loading includes 12,470 kg of N runoff from crop production (based on SWAT calculations), 1,377 kg of N from ammonia deposition, and 33 kg of leached N (from the nitrous oxide emission calculation in Equation A.2). Total farm net return is \$507,909 Table 4.2. Total crop costs are \$356,161 and crop sales are \$611,222. The total net return includes return to fixed factors such as land, management, and owner capital. The cost of land rent, owner labor, interest on owner capital, and other overhead costs are excluded. The nutrient sources for crop production include manure application, commercial fertilizer, ammonia deposition on land, and legume fixation. Of the total ammonia deposited on land 37.5% will be delivered to the surface water, however, 62.5% of the ammonia deposition is available for crop production as a source for N (see Appendix A). The amount of manure that is being sold is selected by the model and it is excluded from the available manure nutrient for crop production. The amount of commercial fertilizer and manure application is also selected by the model based on the type of crop that is being produced and legume fixation of the produced crops if applicable. In the baseline scenario, the amounts of commercial fertilizers used on-farm are 25, 8.9, and 28.4 mt of N, P, and K, respectively. Of the total ammonia deposited on land 62.5% (1,377 kg of N) is also available for crop production. In addition, all manure that is produced on farm including 1.55 million liters of liquid manure, 300 mt tons of dairy solid, and 376 mt tons of broiler litter are applied on land. One hundred twenty-two ha of continuous corn (grain and silage) and 272 ha of two years corn (grain)-three years alfalfa are the rotations used in the baseline scenario. Total corn grain and alfalfa crops produced on-farm are sold, while all corn silage produced on-farm is fed to the cows.

Table 4.1: Environmental output of the baseline scenario compared to literature values

	Unit	Baseline value	Literature value	Citation
N	Kg/ha	34.7	45.85	Bosch et al. (2018)
P	Kg/ha	0.44	0.67	CAST (2019)
Ammonia	Kg/head per year	6.12[a]	13.1 - 55.5	Pinder et al. (2003)
	g/bird/day	0.07[b]	0.027 - 2.17	Pescatore et al. (2005)
GHG	Kg-CO2/Kg of milk	1.7[c]	0.53 - 1.23	Rotz et al. (2010), Thoma et al. (2013a)

[a] Including emissions from housing area, lagoon, and land application.
[b] Including emissions from housing area, cake storage, and land application.
[c] Only dairy GHG. Including GHG emission from purchased feeds.

The total diet cost and total milk production are \$30,649 and 1,049 mt, respectively. The diet ingredients for dairy cows are purchased as required except for the corn silage. The diet for the baseline consists of 72% forage (corn silage and purchased grass silage), and 28% non-forage feed including corn gluten meal, sunflower seeds, wheat middling, and meat and bone meal. The number of broiler houses is at its allowable maximum of one with the total net returns of \$49,017 per year.

4.1.2 Maximizing Nitrogen, Phosphorus, Ammonia or GHG Reduction

Nitrogen

The individual N reduction scenarios include 5 to 25% reductions. In these scenarios, the total N loading including N loaded from crop production, ammonia deposition, and leached nitrous-oxide from manure production is reduced relative to the baseline. The total farm net return falls as reduction increases. Total farm net return shows a drop from 0.77% (to $503,999) to 4.88% (to $483,128) for 5 to 25% reductions in N, respectively (Figure 4.1). N reduction occurs by increasing CRP and replacing corn-alfalfa rotation with more continuous corn production. Corn production remains unchanged (236 ha) over the 5 to 25% N reduction scenarios. However, alfalfa production is reduced by 17% (to 136 ha) to 91% (to 14 ha) over the 5 to 25% N reduction scenarios, and there is an incremental increase in land retirement as CRP up to the maximum allowable amount of 100 ha at 25% N reduction. Thus, total crop production falls 37.5% to 250 ha at 25% reduction leaving 50 ha of land idled in addition to the 100 ha of CRP. However, the amount of corn that is produced remains the same by replacing corn-alfalfa rotation with more continuous corn production. CRP is the only BMP used to reduce the N loading from the land. On average for the five scenarios, commercial fertilizer application for P and K drops by 40% and 73% relative to the baseline, however, N application increases by 0.8% mainly due to the substitution of corn for alfalfa.

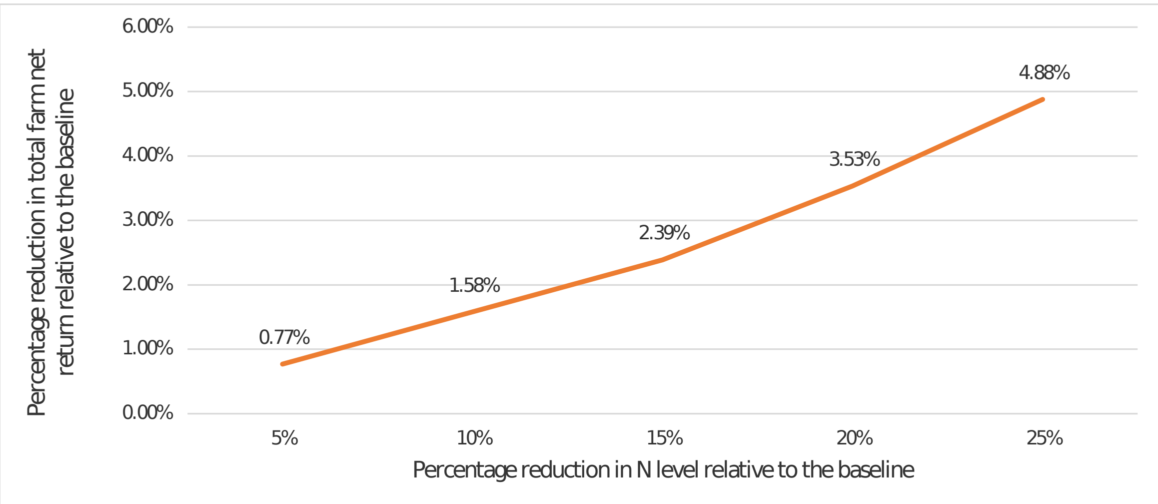

Figure 4.1: Dairy farm net returns variations with respect to reductions in individual N loading

P emissions drop from 1.7 to 8.7% as N decreases from 5 to 25% (Figure 4.2) due to less crop production. Ammonia drops by 3.9% with the initial 5% reduction in N (Figure 4.2) due to a 1% reduction (8.4 mt reduction) in forage feeding. There are two main reasons for relatively small reduction in ammonia production. First, the total N loading is defined mainly based on crop production loadings and only 10% of the total N loss comes from ammonia deposition. Second, it is relatively less expensive to reduce the N loading through crop production practices rather than changing the diet composition. Therefore, the main reduction in N comes from changes in crop production rather than diet optimization. GHG emissions drop from 1% to 13% as N decreases from 5 to 25%. The main reason for the GHG decline is reduction in crop production which results in less CO_2 emissions from crop production. The number of broilers and dairy cows remains constant as N reduction increases, which results in the constant amount of manure produced and livestock net returns.

Phosphorus

The individual P reduction scenarios consist of 5 to 25% incremental reductions from baseline. Total farm net returns (Figure 4.3) decrease by 1.54 to 7.69% as P reduction increases from 5 to 25%. As shown in Figure 4.4, N drops from 1.5 to 7.8% as P decreases from 5 to 25%, which enables farmers to manage the reduction of both N and P (Tozer

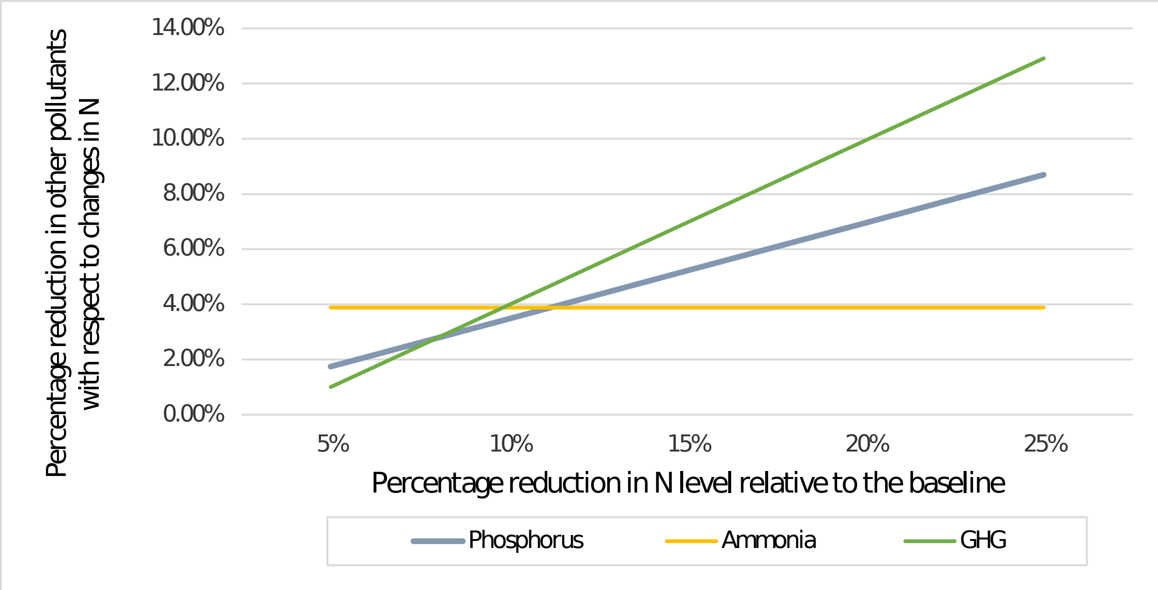

Figure 4.2: P, ammonia, and GHG reduction under individual N reduction scenarios

and Stokes, 2001). On the other hand, ammonia and GHG remain unchanged.

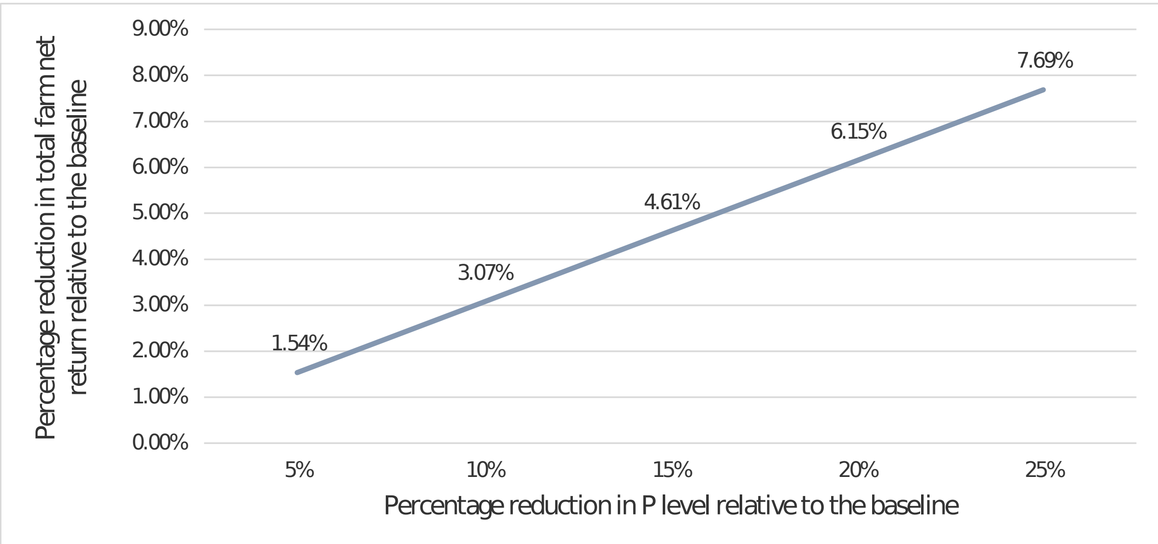

Figure 4.3: Total farm net returns reductions with respect to reductions in individual P loading

The main driving force for P reduction is the change in the composition of the crop produced on farm. For instance, continuous corn production is replaced with alfalfa production in rotation with corn. In particular, average corn grain production drops by 20% (from 221 to 160 ha)

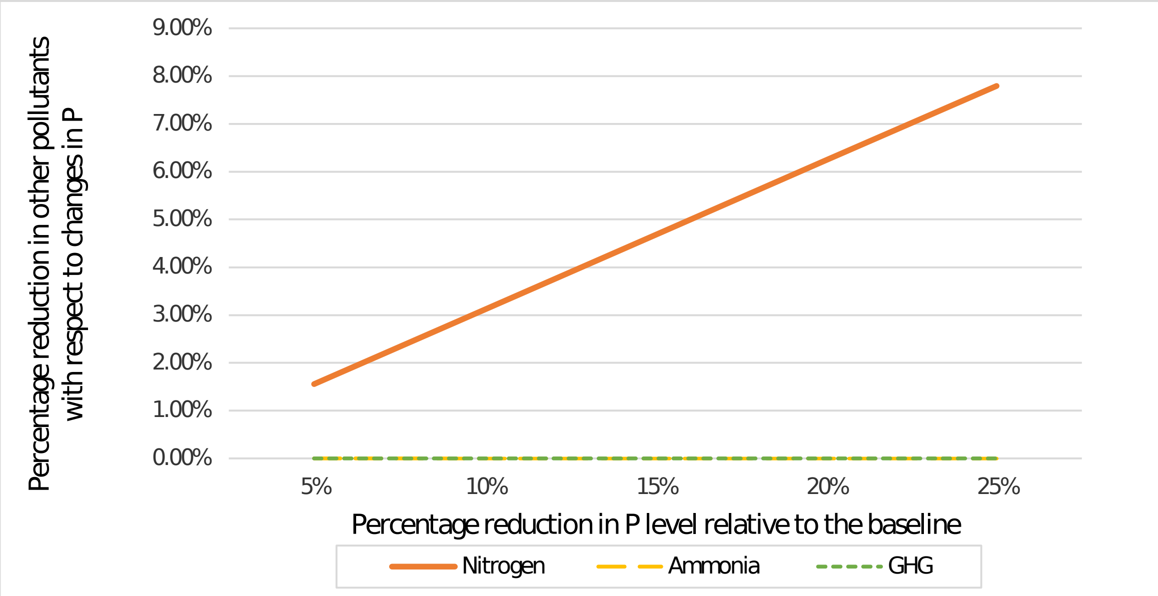

Figure 4.4: N, ammonia, and GHG reduction under individual P reduction scenarios

while average alfalfa production increases by 30%, (from 177 to 240 ha) relative to the baseline. There are no changes in BMPs relative to the baseline. No-tillage farming is the only BMP used for crop production, which is the same as the baseline. In addition, the change in crop production causes a change in commercial fertilizer usage. For 25% reduction in P, the amount of N and P fertilizer applied decreased by 27 and 1.3% (from 22.8 to 13.7 mt of N and 8.9 to 8.7 mt of P), respectively. K application increased by 23.4% (from 30.6 to 39.5 mt) due to an increase in alfalfa production. Results from individual P reduction scenarios show no impact on broiler and dairy production.

Ammonia

The 5 to 25% ammonia reductions reduce the total farm net returns by 0.24 to 6.60% (Figure 4.5) due to a reduction in broiler production and increase in diet cost. Net returns reductions were smaller than those recorded for the P reduction scenario but larger than under those recorded for the N reduction scenario. Over the entire 5 to 25% ammonia reduction, GHG and P emissions remain relatively unchanged, however, N emissions drop by amounts ranging from 0.6% to 2.5% relative to the baseline (Figure 4.6). In general, ammonia reduction comes from two different sources. The main change is the gradual reduction in broiler production, which declines by 0.3 of a house at 25% ammonia reduction. Secondarily, changes in diet composition from 67% forage concentration to 57% forage contribute to the reduction over the five scenarios. The percentage of the forage feed is calculated based on the total dry matter intake. Reducing forage in the diet reduces N excretion, which in turn reduces ammonia emissions because ammonia emission factors are based on percentage of N loss. While the change in the diet composition results in a change in the composition of purchased feeds, which, in turn, causes a reduction in livestock GHG emission, it also increases GHG emission from crop production leaving the net GHG emission unchanged.

Dairy production shows no change relative to baseline. Corn production increased by 3.1% (from 2,177 to 2,245 mt) while alfalfa production decreased slightly from 1,239 to 1,234 mt. The change in the amount of crop production is due to change in crop rotation. In particular, 5 ha of continuous corn silage in the baseline scenario is replaced by 5 ha of corn grain and 13 ha of two years corn (grain)-three years alfalfa production in the baseline scenario is replaced by 13 ha of two years corn (silage)-

three years alfalfa rotation for the 5% ammonia reduction scenario. As mentioned in chapter 3 (crop production section), changing corn rotation from continuous to two years corn-three years alfalfa increases the corn yield by 11%. Therefore, by changing the corn rotation we are producing more corn per ha while the ha under corn cultivation remains unchanged (236 ha of corn (silage and grain) and 163 ha of alfalfa production). N fertilizer application increases by 9.4% from 25.4 to 27.8 mt of N and K application increased by 10.2% from 28.3 to 31.2 mt of K, over the five ammonia reduction scenarios. P application also increased by 40% from 8.9 to 12.5 mt of P. The variation in fertilizer applications is the result of the change in corn rotation as discussed previously, which resulted in fixed corn acreage and higher yields of corn.

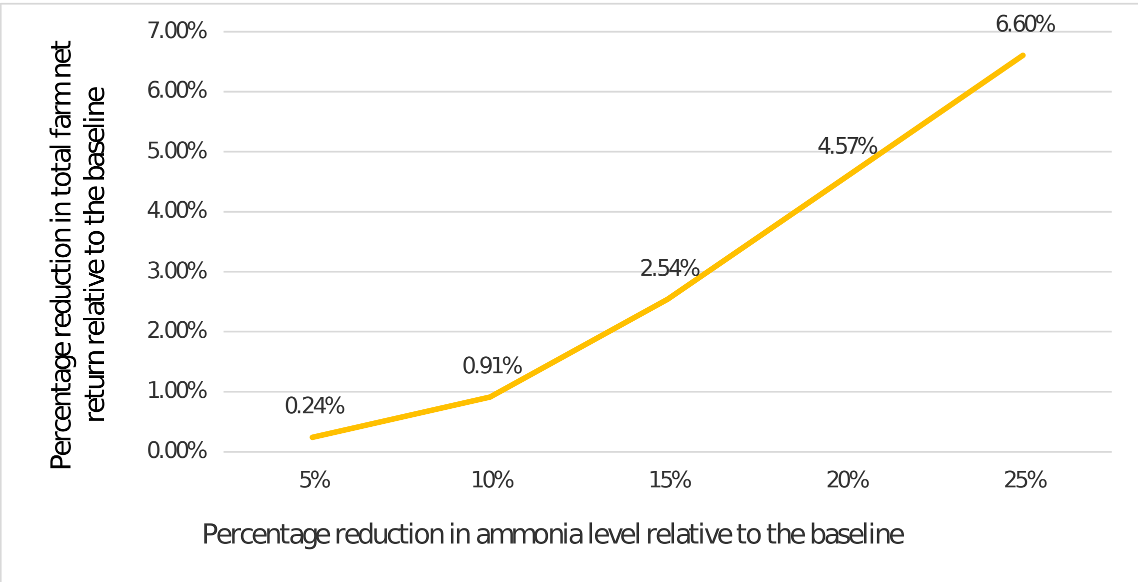

Figure 4.5: Total farm net returns variations with respect to reductions in individual ammonia emission

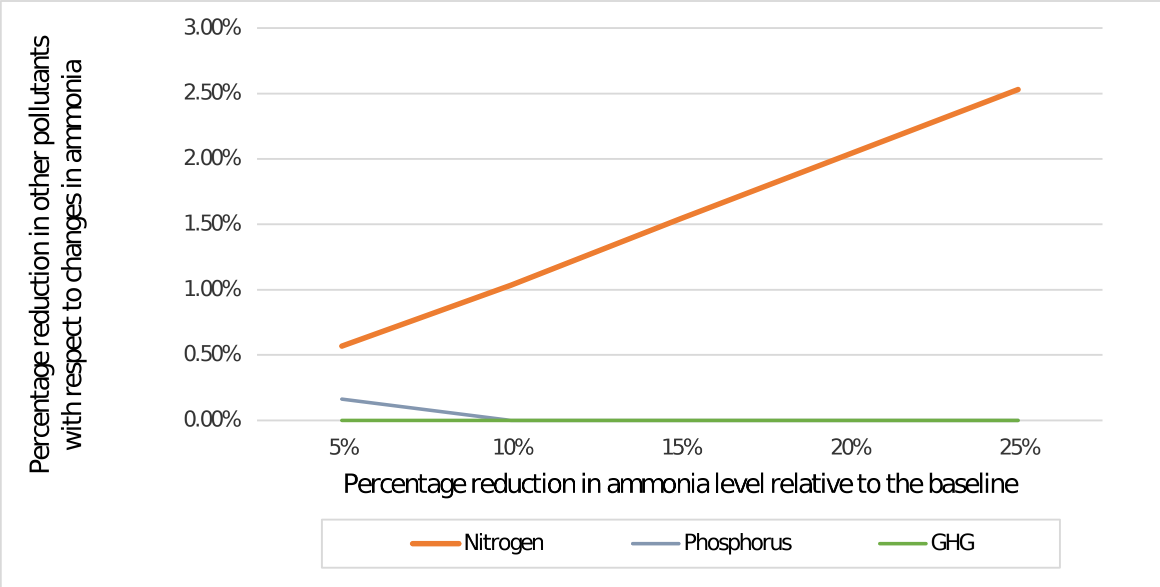

Figure 4.6: N, P, and GHG reductions under individual ammonia reduction scenarios

GHG

Five to 25% GHG emission reductions from baseline result in 0.41 to 2.27% reductions in total net returns (Figure 4.7). N and P loadings drop about 0.6% and 1.8% with respect to 25% reduction in GHG while ammonia remains unchanged (Figure 4.8). GHG emission reduction is mainly achieved by changes in the diet, which increase diet costs for dairy cows and reduce overall net return. At 5 to 25% reduction in GHG, the share of the forage feeds in the overall diet for cows dropped from 70% to 40% (based on percentage of the dry matter intake). This result is similar to findings from previous studies by Belflower et al. (2012) and Lizarralde et al. (2014). Farm produced corn silage and purchased grass silage as the main feeding options were replaced with other non-forage feeds such as sunflower seeds, corn gluten meal, and wheat middling.

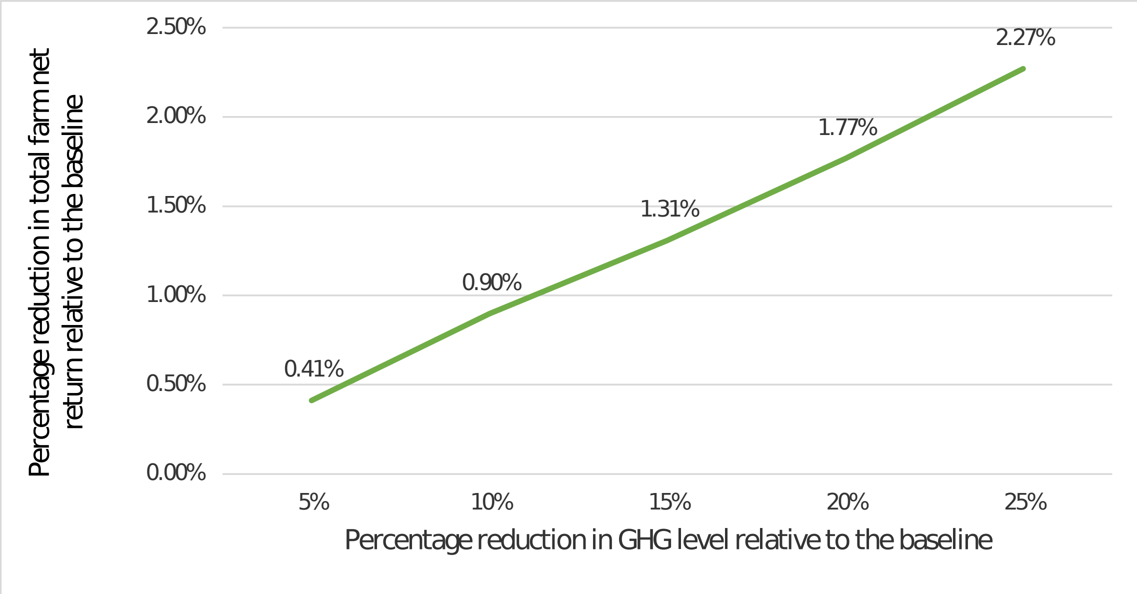

Figure 4.7: Total farm net returns variation with respect to reductions in individual GHG emission

Alfalfa production increases by 3 ha from 165 to 168 (1.8%) as GHG is reduced by 5 to 25%. Crop production net return (calculated by crop sales minus crop production costs) shows an incremental increase from \$347,700 to \$353,788 at 25% GHG reduction due to an increase in alfalfa production and sale. For 5 to 25% reduction in GHG emissions, the amount of N fertilizer applications drop from 25 mt to 24.7 mt at 5% reduction and 24.1 mt at 25% reduction (1.2 to 3.6% reductions relative to the baseline). P applications are reduced from 8.9 mt in the baseline to 8.8 mt for 5% GHG reduction and to 8.5 mt for 25% GHG reduction (1.1 to 4.5% reductions relative to the baseline), and K applications are reduced from 28.4 mt in the baseline to 28.2 mt for 5% GHG reductions and to 27.9 mt for 25% GHG reduction (0.7 to 1.8% reductions relative to the baseline). The reduction in commercial fertilizer applications are due to a shift in crop production from corn silage to alfalfa produc-

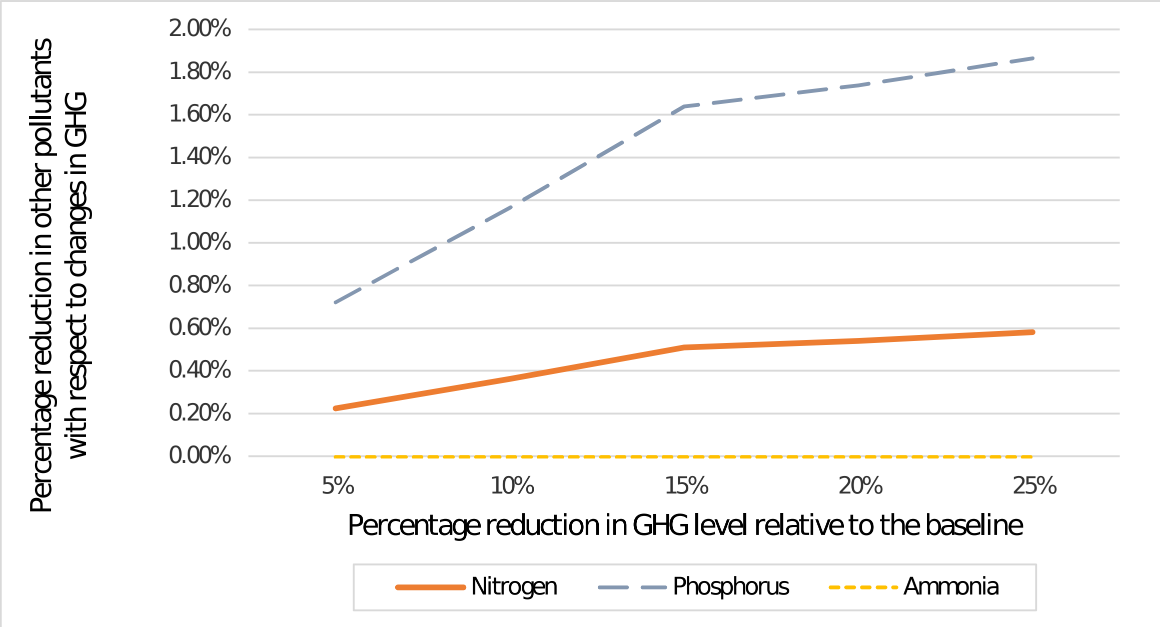

Figure 4.8: N, P, and ammonia reductions under individual GHG reduction scenarios

tion. The broiler house produces at its maximum capacity with the net returns of $49,017. Milk production shows no change relative to the baseline with the total of 1,049 mt of milk production. However, dairy production net return drops from $325,364 in the baseline to $318,308 at 5% GHG reduction to $301,004 at 25% GHG reduction (2.1 to 7.2% reductions relative to the baseline) due to added costs of changing the diet. In particular, total diet cost increases from $30,648 in the baseline to $37,705 at 5% GHG reduction to $55,009 at 25% GHG reduction.

4.1.3 Simultaneous Reductions of N, P, Ammonia and GHG

Increasing simultaneous reductions of N, P, ammonia, and GHG cause total net returns to decrease as well. Net returns decline by 2% to $497,442 for a 5% reduction in emissions and by 16% to $426,376 for a 25% reduction in emissions (Figure 4.9). All pollutants show exact incremental reductions from 5 to 25% relative to the baseline (Figure 4.9). Crop production net return (calculated by crop sales minus crop production costs) drops by 3.2% to $332,590 under 5% joint reduction and by 21.8% to $268,746 under 25% joint reduction, mainly due to a drop in land under cultivation and increase in land retirement under CRP up to the allowable CRP maximum of 100 hectares. Corn production drops from 225 to 177 ha over 5 to 25% joint reductions. Alfalfa production also decreased from 155 to 122 ha over the five reduction scenarios. The ratio of forage in dairy cow's diet composition declines from 67% to 35% over 5 to 25% reductions. Dairy milk and dairy manure production remain unchanged, however, at the 25% joint emissions reduction, broiler production declines by 30%. N, P, and K fertilizer applications drop by 5.7, 14.5, and 9%, to 23.6, 7.6, and 25.8 mt, respectively, for 5% joint reduction and by 24.7, 28, and 29% to 19, 6.4, and 20 mt, respectively, for 25% joint reduction.

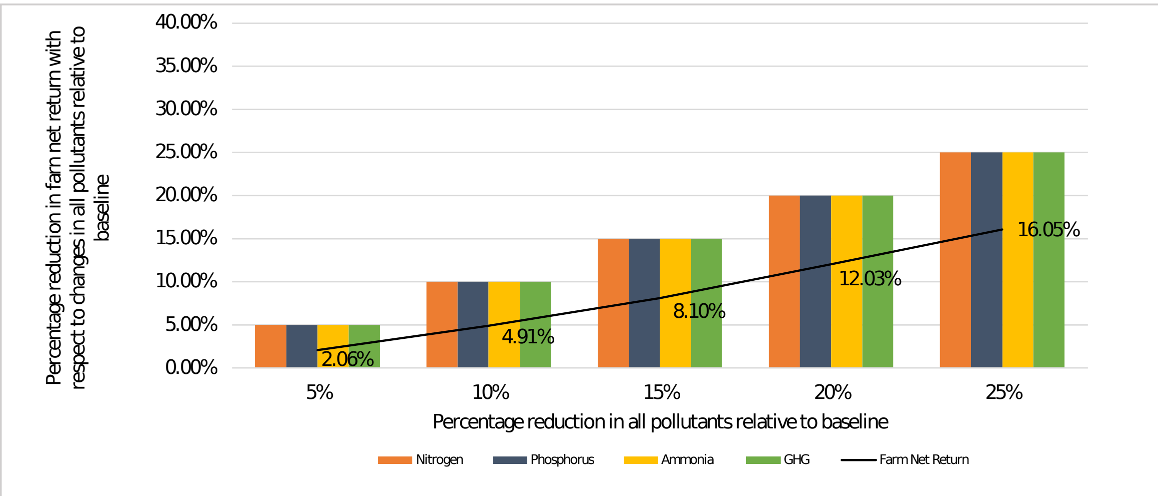

Figure 4.9: Percentage reduction of net returns when N, P, ammonia, and GHG emissions are reduced simultaneously

In comparison with the ammonia and P reductions, N and GHG reductions can be achieved by sacrificing fewer net returns. The results also demonstrate that corn grain, alfalfa, and corn silage are the most profitable crops, respectively. In addition, 2-year corn 3-year alfalfa and continuous corn (grain and silage) are the most profitable rotations for crop production, respectively. Within all BMP alternatives, CRP is the most effective BMP. The major drivers of reduction in N and P are the reduction in total crop production and increase in land retirement as CRP. On the other hand, major drivers for GHG and ammonia reductions are the change in diet composition and reduction in broiler production, respectively.

4.2 Analysis of the ϵ-constraint Optimization

The results for this optimization show that the value for the net return is \$503,603 Table 4.3, which is 0.85% less than the net returns for the baseline scenario of NLP optimization. The results also show 0.35% reduction for N emissions to 13,831 kg, 1.14% reduction for P to 173 kg, and 10% reduction for GHG to 2,985,312 kg, relative to the baseline. However, ammonia remains at the same level of 14,381 kg. This indicates that for the given reduction in farm returns a larger percentage reduction in GHG is achieved relative to N, P, and ammonia. Total crop production remains constant at 400 ha, however, there is a modest shift from continuous corn to corn-alfalfa rotation. In the NLP baseline scenario, we had 128 ha of continuous corn and 272 ha of corn-alfalfa rotation, however, under the ϵ-constraint optimization, we have 122 ha of continuous corn and 278 ha of corn-alfalfa rotation. N, P , and K fertilizer applications decreased by 2% to 24.5 mt, 2.2% to 8.7 mt, and 1.1% to 28.1 mt, respectively, relative to the NLP baseline. Manure production is similar to the baseline and all the manure that is produced on farm is applied on land. The results also confirm that the most profitable crops are corn grain, alfalfa, and corn silage, respectively, with continuous corn and corn-alfalfa rotations similar to NLP optimization. No-tillage farming is the BMP used for crop production. Based on dry matter intake, the diet for the cows consists of 66% forage and 34% non-forage. Total amount of milk production is 1,049 mt. Broiler production is at its maximum level with $49,018 net return.

The weights used for ϵ determine the value attached to reductions in environmental loadings (Equation 3.11). Sensitivity analysis was conducted to show how environmental emissions of N, P, ammonia, and GHG would be affected by changing the weights for ϵ (Table 4.4). We obtain the results by setting the weight of ϵ for each constrained objective first to 1, then 10^{-1}, 10^{-3}, 10^{-6}, and finally 10^{-9}, thereby allowing slacks associated with the environmental constraints to vary. The results in Table 4.4 indicate very small fluctuations in N loadings for variations in ϵ from the original $\epsilon = 10^{-3}$, no change in P, ammonia, and GHG emissions while total net returns decrease with higher values of ϵ. The similarity of results indicates that much larger changes in the weights of the slack variables for environmental emissions are needed to show trade-offs between environmental loadings and net returns.

4.2.1 Sensitivity Analysis of the Farm Model

Previous studies show that BMPs are effective ways to reduce farm loading (Xu et al., 2020). However, the only BMP employed in our study to reduce farm loadings relative to the baseline is CRP. No-till is employed in the baseline as it has a negative cost. In order to examine the robustness of the results, we implemented a sensitivity analysis to further investigate the effectiveness of the BMPs in the farm model. We reduced the cost of all BMPs to zero. No-tillage cost, which was negative in the baseline, was also set to zero. The results indicate that for 25% reduction in N, 227 ha of nutrient management and no-tillage, 22 ha of nutrient management with manure and no-tillage, 100 ha of CRP, and 4 ha of pasture buffers are employed. For 25% P reduction, 329 ha of nutrient management and no-till, 25 ha of nutrient management with manure and no-till, and 45 ha of crop buffers (in grass cover with neither conventional tillage nor no-tillage farming) are used to reduce loadings. For 25% joint reduction, 194 ha of nutrient management and no-tillage, 16 ha of nutrient management with manure and no-tillage, and 100 ha of CRP are used. In conclusion, with zero cost BMPs and for N and P loadings reduction, no-tillage farming, CRP, nutrient management with and without manure, and crop buffers are most effective.

Table 4.2: Summary of the results for the baseline scenario

Variable	**Value**
Farm net return ($)	507,909
Broiler net rerturn ($)	49,018
Crop production net return($)[a]	255,062
Crop sales ($)	611,223
Crop costs ($)	356,161
Dairy production net return ($)[b]	203,829
Milk revenue ($)	360,963
Gross revenue ($)	150,461
Fixed cost ($)	271,997
Manure net revenue ($)	-4,949[c]
Total diet cost[d] ($)	30,648
Total milk production (mt)	1,049
Hectares of crops produced on-farm	
Corn grain	231
Corn silage	6
Alfalfa	163
Manure produced on-farm (per unit)[e]	
Dairy liquid (ML)[f]	1.55
Dairy solid (mt)[g]	300
Broiler litter (mt)[g]	376
Purchased feeds (mt)	
Corn gluten meal	29.60
Grass silage	138.34
Sunflower seed	1.37
Wheat middlings	133.47
Meat and Bone meal	0.09
Average number of the dairy cows in each month	
One-year old heifer	20
Two-year old heifer [h]	22
Three-year old cow	20[i]
Four-year old cow	20[i]
Five-year old cow	40[i]

a Crop production net return is calculated as:
$CRNetReturn = \sum_f Sld(f) * SPR(f) - \sum_f x(f) * TC(f) - \sum_n C(n) * NPR(n) - TBMPC$. (see Table 3.1 for parameters)

b Dairy production net return is calculated as:
$DPNetReturn = \sum_u S(u) * MSP(u) - \sum_u A(u) * MAC(u) + Tmilk * MPR - \sum_c x(c) * FC + \sum_c x(c) * GR - \sum_f Prc(f) * BPR(f)$ (see Table 3.1 for parameters)

c Calculated by subtracting manure application costs from manure sales.
d Cost of purchased feed for dairy cow's diet. To avoid double calculations this cost is not included in crop production net returns.
e All manure produced on-farm is spread on land
f In million liters
g In metric tons
h Eight percent of the two-year old heifers are considered to produce milk.
i This is the average of 10 months of milking period. We considered two months of dry period for dairy cows.

Table 4.3: The results generated by ϵ-constrained optimization and the percentage change relative to baseline

	Total Farm Value	Value per unit	% Change
Net returns	503,603 ($)	1,259 ($/ha)	-0.85
N	13,831 (kg)	34 (kg/ha)	-0.35
P	173 (kg)	0.43 (kg/ha)	-1.14
Dairy ammonia	$14{,}381^a$ (kg)	6.12 (kg/head per year)	0
Broiler ammonia		0.07 (g/bird/day)	
GHG[b]	2,985,312 (kg)	1.5^c (Kg-CO2/Kg of milk)	-10

a Total ammonia
b Total GHG emission from crop and dairy productions
c This is calculated based on the GHG emission from dairy production that is 1,605,940 kg

Table 4.4: Sensitivity analysis of the epsilon-constraint model

Variable	1	10^{-1}	10^{-3}	10^{-6}	10^{-9}
Total hectare of crop production	400	400	400	400	400
Total net return ($)	476,532	476,530	503,603	503,577	503,598
N loading (kg)	13,829	13,830	13,831	13,828	13,830
P loading (kg)	173	173	173	173	173
Ammonia loading (kg)	14,382	14,382	14,382	14,382	14,382
GHG emission (kg)	2,985,312	2,985,312	2,985,312	2,985,312	2,985,312

Chapter 5

Summary and Conclusion

Because of the importance of water and air pollution abatement in the agricultural sector, farmers need options to reduce pollution that are feasible and low cost. Consequently, they seek to use different farm practices in order to maximize their net returns while reducing pollution levels to a satisfactory level. This study conducts two approaches, ϵ-constraint method and non-linear programming (NLP), to study the trade-offs associated with increasing farm net returns and reducing the most important pollutants generated by agricultural activities. The ϵ-constraint method is computationally more efficient, however, it provides little information about the trade-off among different objectives. On the other hand, the NLP approach allows us to examine different combinations of emissions reductions in order to see the trade-offs between emission reductions and net returns.

The results of this study show how net return changes with respect to different reduction levels for N, P, ammonia, and GHG. An increasing marginal rate of substitution between net returns and joint pollution reductions is confirmed by the results (Figure 4.9). The reductions of GHG are least costly (.41 and 2.27% reductions in net returns for 5 and 25% reductions in GHG, respectively) while P is most costly (1.54 and 7.69% reductions in net returns for 5 and 25% reductions in P, respectively). N reductions (.77 and 4.89% reductions in net returns for 5 and 25% reductions in N, respectively, and ammonia reductions (.24 and 6.6% reductions in net returns for 5 and 25% reductions in ammonia, respectively, are intermediate in cost relative to GHG and P. However, reducing one emission may result in reduction of others as well. For instance, for 5 to 25% reductions in N we have 1.7 to 8.7% reductions in P, 3.9% reduction in ammonia, and 1 to 13% reductions in GHG. For 5 to 25% reductions in P, N will be reduced by 1.5 to 7.8%. Five to 25% reductions in ammonia causes 0.6 to 2.5% reductions in N loading. For 5 to 25% reduction in GHG we have 0.2 to 0.6% reductions in N and 0.7 to 1.8% reductions in P. Depending on the target pollutant, reduction strategies can be different. In general, for N reduction land retirement under CRP and producing more continuous corn and less alfalfa are the most effective strategies. However, the results indicate that for P reduction increasing corn-alfalfa rotation is more effective. For ammonia and GHG emissions, the most effective strategy is to change the diet composition of the dairy cows by feeding more non-forage feeds. Reducing broiler production is also another efficient way to reduce ammonia.

Using results from this study farmers and farm extension workers can identify best practices to reduce targeted pollutants. In addition, the comprehensive farm model can be used by different farmers with different land, labor, and machinery capacities to develop a customized plan for their annual production. Natural resource managers at the state and federal levels can use the results of this study to define comprehensive programs to reduce multiple pollutants from dairy farms. For instance, using results from different scenarios natural resource managers can design practical cost share and technical assistance programs. The results can help policymakers to understand trade-offs among water and air pollutant reduction in dairy farming. Moreover, from a research economist perspective, the inclusive farm model carried out in this study can be used to further analyze the environmental impacts of different farm types.

Several extensions of this research would be helpful to gain further insight into costs of reducing emissions from dairy farms. First, the ϵ-constraint optimization procedure could be further examined by varying the weights attached to each environmental objective and by using a larger range of weights for each objective. In this way the ϵ-constraint optimization procedure might provide more insight into the trade-offs between each type of environmental emission and net returns. Second, the ratio of dairy cows to cropland should be varied to see how optimal strategies change as the available land per cow declines. This study assumed 5 ha of cropland per cow. However, many dairies in the eastern U.S. have much less land available per cow. Third, further work is needed to determine how Best Management Practices including nutrient management, cover crops, and stream buffers can play a larger role in emissions reduction strategies.

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Appendix A

Environmental calculations

In this section, we present the environmental calculations in more detail. Ammonia as one of the important pollutants has two general reduction strategies. 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% (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).

Figure 3.3 shows the total ammonia emissions from the dairy farm and broiler house at each stage (USEPA, 2004). As shown in Figure 3.3 much of the ammonia emission occurs at manure collection and storage stages in the dairy production system (71% and 20%, respectively). Equation A.1 was used to calculate the ammonia emissions at each stage (USEPA, 2004). Ammonia emission factors are expressed as a percentage of N loss as ammonia. Particularly, as mentioned before, a cow excretes 21.1 thousand liters of liquid manure annually, which consists of 70 kg of N. Of this total, 23.5% (16.5 kg of N) is emitted as ammonia at the housing area. Of the remaining 53.5 kg of N that is flushed into the lagoon, about 71% (38 kg of N) is emitted as ammonia before land application. From the remaining 15.5 kg N about 24% (3.7 kg) will be emitted after land application.

$$TAm = (\sum_i N_i * EF_i) * 17/14 \tag{A.1}$$

Where,

TAm: Total farm ammonia emissions from manure

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

EF_i: ammonia emission factor at every stage i (Figure 3.3), and

17/14: NH_3/N conversion factor.

In addition, as Loubet et al. (2009) state, within a 2 km distance of an ammonia emission source, about 2 - 60% of the ammonia emitted will be deposited on land. In this regard, we assumed an average deposition of 31% in the model. Furthermore, deposited ammonia on land will be loaded into surface waters at a rate of one-quarter to one-half (Sheeder et al., 2002). We assumed 37.5% ratio meaning that about 11.6% of ammonia emissions is delivered as N to surface water in addition to loadings from crop production. For instance, total ammonia emitted from housing (16.5 kg of N), storage lagoon (38 kg of N), and land application (3.7 kg of N) sums to 58.2 kg of N. Applying the 31% deposition rule we have 18.04 kg deposited of which 37.5% (Loubet et al., 2009) (6.77 kg) is delivered to surface water.

The GHG emissions include nitrous oxide, enteric methane, manure methane, and carbon dioxide emissions from crop production. The definition and values of the scalars used in Equation A.2 through Equation A.6 are expressed in Table A.1. Total nitrous oxide emissions are calculated using IPCC (2006) equations as follows:

Table A.1: Scalars used for calculating environmental impact from dairy cow management

Scalar	Unit	Definition	Value
EF_{MMT}(k)	Percent of N loss	Ammonia emission factor at every stage	See Figure 3.3
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	%	Percentage of managed manure N leached	28.105
Fracvol	%	Percentage of managed manure N volatilized	17.3
BO	m3 CH4 / kg VS	Maximum emission rate	1
MCF	%	Average methane conversion efficiency	17.3
CF_1		CO2-equivalent warming potential for methane	25
CF_1		CO2-equivalent warming potential for nitrous oxide	298

$$TNO = \sum_{c,m}((NE_{c,m} * EF3 * \frac{44}{28} + NE_{c,m} * FracVol * EF4 * \frac{44}{28}$$
$$+NE_{c,m} * Ef5 * Fracleach * (44/28)) * pop_{c,m} * day_m) \quad (A.2)$$

Where,

TNO: Total nitrous oxide produced on the farm in kg

$NE_{c,m}$: Total N excreted (kg for each cow category at each month). See Equation A.3

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

day_m: Number of days in each month

$$NE_{a,m} = (\sum_f dmi_{c,m,f} * feednut_{f,CP} * 0.16 * 1000) - cnex_{m,c} * 0.16)/1000 \quad (A.3)$$

Where,

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

$feednut_{f,CP}$: Proportion of crude protein in each feed as a decimal fraction

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

Total methane emissions are shown in Equation A.4 as a function of enteric methane emissions plus manure methane emissions.

$$TMT = \sum_{c,m}(CH4e_{c,m} + CH4m_{c,m}) \tag{A.4}$$

Where,

TMT: Total methane production on farm (kg)

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

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

Equation A.5 shows the calculation of enteric methane as a function of feed ingredients in the diet (Moe and Tyrrell, 1979).

$$\begin{split} CH4e_{c,m} = ((3.51 + 0.511 * \sum_{f} dmi_{c,m,f} * feednut_{f,NSC} + 1.74 * \sum_{f} dmi_{c,m,f} * HC_f \\ +2.65 * \sum_{f} dmi_{c,m,f} * Cell_f) * pop_{c,m} * days_m) \end{split} \tag{A.5}$$

Where,

$feednut_{f,NSC}$: Proportion of nonstructural carbohydrates in each feed as a decimal fraction

HC_f: Proportion of hemicellulose in each feed as a decimal fraction

$Cell_f$: Proportion of cellulose in each feed as a decimal fraction

Equation A.6 shows the calculation of manure methane as a function of digestible energy consumed plus ash concentration by cow category (IPCC, 2006).

$$CH4m_{c,m} = VS_{c,m} * pop_{c,m} * days_m * Bo * 0.67 * (MCF/100) \quad \text{(A.6)}$$

Where,

$VS_{c,m}$: Volatile solid excreted in kg for each cow category in each month. See Equation A.7

$$VS_{c,m} = ((\sum_f dmi_{c,m,f} * feednut_{f,GE}) * (1 - DigE_{c,m}))$$
$$+(0.04 * \sum_f (dmi_{c,m,f} * feednut_{f,GE})) * ((1 - AshC_{c,m})/18.45) \quad \text{(A.7)}$$

Where,

$feednut_{f,GE}$: Proportion of Gross Energy in each feed as a decimal fraction

$DigE_{c,m}$: Proportion of digestible energy consumed by each cow category in each month as a decimal fraction

$AshC_{c,m}$: Proportion of ash concentration in each cow category in each month as a decimal fraction

In particular, we assume a cow excretes 0.5 kg of N per day with a total of 182.5 kg of N per year (365 days). According to Equation A.2, the total nitrous oxide produced on farm by a cow is equal to 3.85 kg per year including 2.75 kg of direct emissions, 0.5 kg of volatilized nitrous oxide, and 0.6 kg of leached nitrous oxide. Crop production is responsible for CO_2 and N_2O emissions for on-farm crop production. We also considered GHG emissions from transporting off-farm feeds as White (2016) suggests. We assumed an average of 1000 km of travel for each purchased crop before they are used as feed (White, 2016). The total GHG emission from the farm is calculated using Equation A.8 (USDA/ERS, 2013, Burek et al., 2014). The total farm GHG emission is reported as (CO_2)-equivalent using IPCC (2007) 100-yr warming potentials.

$$TGHG = \sum_f x(f)*CO_2(f)+\sum_f p(f)*CO_2(f)+CF_1*TMT+CF_2*TNO \tag{A.8}$$

Where,

$x(f)$: Kg of crop f produced on farm that can be sold, used as feed, or stored

$CO_2(f)$: kg of GHG emitted for production/transportation of each crop f (see Table 3.4 for the values. Same factors used for farm produced and purchased crops)

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

CF_1: CO_2-equivalent warming potential for methane (See Table A.1)

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

CF_2: CO_2-equivalent warming potential for nitrous oxide (See Table A.1)

TNO: Total nitrous oxide produced on farm in kg

The last category of environmental calculations includes N and P loading from crop production. The SWAT-VSA model produced estimates of crop loadings in the study area (Bosch et al., 2018, Easton et al., 2008, Collick et al., 2015). Table 3.4 shows all loadings and emissions from crop production for each on-farm crop. To calculate total farm N (TNit) and P (TPhs) loadings we used Equation A.9 and Equation A.10.

$$TNit = \sum_{f} x(f) * Nload(f) + TAmToWater + LeachedNitrous \quad (A.9)$$

Where

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

$Nload(f)$: N loaded (kg/ha) for each crop as estimated by SWAT (see Table 3.4)

$TAmToWater$: Total kg of ammonia loaded into water as N equivalents. It is calculated by multiplying total ammonia production (TAM Equation A.1) by 31% to obtain the total amount of ammonia deposition. Then, we multiply the result by the percentage of the ammonia deposition that is delivered to surface water as N that is equal to 37.5%.

$LeachedNitrous$: Total kg of manure N losses due to leaching during solid and liquid storage of manure (IPCC, 2006) (see Equation A.2).

$$TPhs = \sum_{f} x(f) * Pload(f) \tag{A.10}$$

Where,

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

$Pload(f)$: P loaded (kg/ha) for each crop as estimated by SWAT (see Table 3.4)