Managing Conflicting Economic and Environmental Metrics in Livestock Manure Management

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Abstract

Dairy farming is a multi-billion USD industry that provides essential food products. At the same time, the millions of animals that this industry oversees generate a massive environmental footprint (affecting air, land, and water quality). Specifically, livestock manure is a carbon- and nutrient-rich waste stream that is routinely used as fertilizer. This practice enables nutrient recycling but also leads to emissions of greenhouse gases and to nutrient pollution of soils and waterbodies. Mitigating these environmental impacts requires investment in manure processing technologies; identifying and prioritizing investment strategies requires understanding inherent conflicts (trade-offs) and synergies that exist between economic and environmental impacts. In this work, we present a conflict analysis and resolution framework that integrates techno-economic analysis (TEA), life cycle assessment (LCA), and supply chain (SC) optimization. We use this framework to investigate deployment scenarios of manure processing pathways in the Upper Yahara watershed region of Wisconsin; here, we evaluate LCA metrics (GHG emissions, ammonia emissions, fossil energy use, and nutrient pollution) and TEA metrics (cost and revenue) for different pathways that include manure collection, storage, application, and processing steps. The LCA and TEA metrics are embedded within a SC optimization model that makes decisions on technology selection and geographical placement and on product transport in the study area. A conflict resolution procedure is used to explore trade-offs associated with these decisions and to identify optimal compromise solutions that best balance trade-offs. Our results reveal that there exist non-obvious conflicts and synergies between the explored metrics that can be exploited to mitigate multiple impacts simultaneously. We also find that the deployment of a diverse set of technologies is needed to fully resolve conflicts. The impact of emerging technologies (ultrafiltration and reverse osmosis) and government incentives is also discussed.

Keywords: conflict resolution, life cycle assessment, techno-economic analysis, supply chain optimization, livestock manure management.

Introduction

The dairy industry provides essential food products (e.g., milk and cheese) but also produces vast amounts of manure. To give some perspective, an average lactating dairy cow can produce 9,500 liters of milk and 19,000 liters of manure in a year.[1] Manure is a waste stream that is difficult to dispose of because it is highly diluted and distributed. Manure is typically disposed of via land application. This practice provides valuable nutrients for crop production (manure is a renewable fertilizer); however, land application of manure also promotes myriad environmental impacts.

Manure is the second largest source of greenhouse gas (GHG) emissions.[2] Ammonia (NH_3) emissions from manure can reach 70% of the excreted nitrogen (N) and can deposit into water ecosystems or transform into nitrous oxide (N_2O), further contributing to climate change.[3] Manure management in livestock operations contributes 71% of the total NH_3 emissions in the U.S.; this surpasses (by far) the 14% contribution of mineral fertilizers, with dairy alone representing 23% of these livestock emissions.[4] There is also evidence that NH_3 emissions have negative impacts on biodiversity and can promote formation of particulate matter in the atmosphere.[5] In addition to affecting air and water quality, N losses reduce availability of nutrients for crop production (increasing fertilizer costs for farmers).

The deployment of manure processing technologies such as anaerobic digestion (AD) and solid-liquid separation (SLS) can help mitigate environmental impacts. AD can be used to recover biogas and this can be used to produce electricity.[6] Biogas can also be purified and be used as renewable compressed natural gas (rCNG) for vehicle transportation. The deployment of AD systems can reduce manure GHG emissions by more than 50%; this reduction is mostly due to mitigation of CH_4 emissions that originate from manure storage.[7] Renewable power obtained from biogas can also offset carbon emissions from grid electricity.[8]

Despite the many environmental benefits of manure processing technologies, their adoption is still limited by high capital, operational, and maintenance costs (e.g., investment might not be feasible for small or even some large operations).[9] Strategies that reduce manure handling and technology costs and increase potential revenues (via sales of recovered products) are needed to promote the widespread adoption. Moreover, policy that incentivizes mitigation of environmental impacts (e.g., via nutrient and carbon credits) and/or recovery of value-added products is needed.

The environmental impacts of manure management pathways can be quantified using life cycle assessment (LCA). The impacts of manure management have typically been explored as a subset of broader LCA studies that focus on the entire value chain of dairy products.[8,10,11] Other LCA studies have evaluated biogas production from manure and a mix of agricultural feedstocks in order to assess GHG emissions and fossil fuel consumption. De Vries et al.[12] evaluated the environmental impacts of manure separation by reverse osmosis; this study found higher overall impacts when compared to management of raw manure but also found reduced GHG emissions and depletion of fossil fuels with the addition of an AD system. Poeschl et al.[13,14] compared different AD systems that process single and mixed feedstocks. The study concluded that straw and corn silage produced the most biogas when evaluating single-feedstock technologies and combining municipal solid waste with agricultural and food residues produced the most biogas within co-digestion technologies. Ebner et al.[15] conducted an LCA for an AD system that co-digests dairy manure and industrial food waste; the study concluded that GHG emissions can be reduced by 70% (compared to conventional treatment of manure and food waste).

Most of these studies have not included an evaluation of inherent conflicts (trade-offs) that exist between environmental and economic metrics of different technology pathways. Process and systems engineering methodologies have been widely used in the field of environmental management to conduct systematic modeling and support decision-making over trade-offs. Applications reported include economic and environmental trade-offs in energy systems,[16–18] process optimization of waste processing technologies,[19–22] conversion of biomass to chemicals,[23] design and improvement in food-energy-water nexus and circular economy,[24–28] etc. Specifically for the organic waste management problem, supply chain network optimization has been used to describe and capture material transformation, logistical issues, and related economic and environmental aspects. Environmental and economic metrics can be further incorporated within conflict resolution (multiobjective) optimization models to systematically analyze inherent trade-offs and to identify solutions that best balance such trade-offs. A fundamental issue that arises here, however, is that the number of metrics to be explored is typically large. Typical LCA optimization studies have targeted up to three metrics; this is because exploring and visualizing the Pareto frontier is not straightforward in higher dimensions.[29–31] Moreover, different stakeholders prioritize metrics differently (e.g., water quality over air quality); as such, it is necessary to identify solutions that can best resolve conflicts.

In this work, we present a conflict analysis and resolution framework that integrates techno-economic analysis (TEA), LCA, and supply chain (SC) optimization. We use this framework to investigate deployment scenarios for technology pathways in the Upper Yahara watershed region of Wisconsin. Here, we evaluate multiple important LCA metrics (GHG emissions, ammonia emissions, fossil energy use, and N/P/K release) and TEA metrics (cost and revenue) for different pathways that include manure collection, storage, application, and processing (anaerobic digestion and solid-liquid separation). The metrics are embedded within a comprehensive SC model that makes decisions on technology selection, sizing, placement and product transport in the study area. A conflict resolution procedure is used to explore trade-offs associated with these decisions and to identify optimal compromise solutions that best balance trade-offs. Our results shed light into key manure processing technologies and management practices that are needed to mitigate specific impacts. The results also reveal that there exist non-obvious conflicts and synergies between the explored metrics that can be exploited to mitigate multiple impacts simultaneously. We also find that the deployment of a diverse set of pathways is needed to fully resolve conflicts. The impact of emerging technologies (ultrafiltration and reverse osmosis) and government incentives on the resolution of conflicts is also discussed.

Computational Framework

The computational framework proposed includes the following components: quantification of environmental and economic metrics, supply chain model, and conflict resolution procedure. The environmental and economic metrics for diverse manure management pathways are evaluated using LCA and TEA approaches. These metrics are then used in an SC optimization model that makes decisions on technology selection/sizing/placement, transportation, and production. Trade-offs are explored by solving the SC model repetitively in order to minimize/maximize individual metrics and construct a pay-off matrix. A conflict resolution procedure is then used to identify an optimal compromise solution that best balances the individual metrics. We note that the main methodological novelty of this study is to combine multiple computational components to quantify and resolve the conflicts between many economic and environmental metrics.

Life Cycle Assessment

An LCA model[32] was used to estimate i) GHG emissions, ii) NH_3 emissions, and iii) depletion of fossil fuels (DFF) for dairy and beef manure management pathways. These environmental metrics include manure collection, storage, processing, and land application steps. In addition, nutrients (N, P and K) reaching the land were tracked. We conducted analysis for a dairy farm with 2,306 animal units (1 AU = 1,000 pound of animal) that manages 1,000 lactating cows, 605 growing heifers, and 286 mature heifers and dry cows) and for a beed farm with 2,478 AU that manages 1,000 bulls and cows, 210 replacement cattle, 750 stocker cattle and 750 finishing cattle. Manure characteristics were estimated for each animal type for dairy[33] and beef[34] and aggregated for the herd (Table S1).

A total of eleven technology pathways were modeled for both dairy and beef farms (Table 1). Manure is collected from the barn in all pathways and then is either directly land applied, stored prior to land application, or processed via sand recovery, AD, mechanical SLS, and liquid manure processing to clean water (SLS + ultrafiltration + reverse osmosis) and then land applied. All technical and economic data for the clean water system throughout all stages (solid-liquid separation, UF and RO) was obtained from a real-life operation system at a dairy facility in the U.S. Manure storage is considered with and without a liner cover and manure is land applied by surface broadcast and injection. Table 1 presents a summary of each pathway; in this context, a technology is defined as a pathway containing different manure handling operation units.

Table 1: Summary of the operational steps included in each technology pathway.

Technology	Processing Unit	Storage Type	Land Application Method
1	None	None	Surface
2	None	Natural crust	Surface
3	Sand recovery	Uncovered	Surface
4	Sand recovery + AD	Uncovered	Surface
5	Sand recovery + AD + SLS	Uncovered	Surface
6	Sand recovery + SLS	Uncovered	Surface
7	None	Covered	Injection
8	Sand recovery + AD	Covered	Surface
9	Sand recovery + AD	Uncovered	Injection
10	Sand recovery + AD	Covered	Injection
11	Sand recovery + AD + SLS + UF + RO	Uncovered	Surface

GHG emissions (expressed in kg CO_2-eq) include methane (CH_4), direct and indirect nitrous oxide (N_2O) from manure, and fossil carbon dioxide (CO_2) from the combustion of fossil fuels used on-farm. Characterization factors for CH_4 and N_2O are 28 and 265, respectively, for a 100-year horizon.[35] NH_3 (expressed in kg) is emitted from manure during collection, storage and land application and DFF (MJ) originates from the use of grid electricity and diesel for machinery operation.

Manure handling operations include collection, storage, and land application steps. Manure is collected daily with a skid steer that operates with diesel. Manure, digestate, and separated manure/digestate liquids and solids are in an open storage for six months before land application in April and October. A mineralization rate (conversion of organic nitrogen to ammonium[36]) of 16% is assumed for the given storage duration.[37] An organic crust is modeled in technology scenarios without manure processing due to higher TS in manure, which decreases CH_4 and NH_3 emissions but increases N_2O emissions.[37] Liner covers of the storage system (a pond) are also modeled. Manure is agitated and then land-applied by surface broadcast with diesel applicators or with manure injection to mitigate NH_3 emissions. In other words, land application requires hauling and thus consumes fossil fuels and generates carbon emissions.

Mechanical SLS is modeled using a screw press that runs on electricity with separation efficiencies reported in Aguirre-villegas et al.[38] A plug-flow digester is used to produce biogas considering a 28-day retention time. Electricity is generated from biogas (65% CH_4 with a LHV of 36 MJ/m^3) at 35% and 50% electric and thermal efficiency, respectively. We note that the final methane production is assumed based on typical methane volumetric compositions, which includes all losses as it is based on empirical data.[39] The digester is heated using 20% of the thermal energy generated during electricity production. It is assumed that the remaining thermal energy is lost. In addition, the digester demands 17% of the daily produced electricity.[32] Total ammoniacal nitrogen (TAN) is increased by 35% due to mineralization during the digestion process.[37] It is assumed that the produced electricity is used on farm with surplus injected into the electricity grid. This electricity is renewable and offsets both the lifecycle GHG emissions and the DFF embedded in grid electricity. The offsets are expressed as metric benefits (negative GHG and DFF).

We consider a pathway that generates clean water from manure (we refer to this as the clean water pathway). This system requires prior AD and consists of three separation systems set up in series: a centrifuge, an ultrafiltration system, and a reverse osmosis system. Centrifugation achieves higher separation efficiencies than screw pressing.[40] After centrifugation, the solid fraction is stored for six months before land application and the liquid digestate is further separated into an untrafiltration concentrate (UFC) stream (containing most of the P) and an ultrafiltration permeate (UFP) stream. After centrifugation, the solid fraction is stored for six months before land application and the liquid digestate is further separated into an ultrafiltration concentrate (UFC) stream and an ultrafiltration permeate (UFP) stream (see Table S2 for separation efficiencies). Equations and emission factors used to estimate GHG, NH_3 emissions and DFF, and total environmental metrics for the eleven technologies are presented in supporting information.

We highlight that different pathways can have steps in common; for instance, AD is a common step in many of them. This highlights the fact that there are complex dependencies between technologies and intermediary products. We also highlight that all pathways generate a nutrient-rich stream that needs to be disposed of. The nature of these streams is different (e.g., contain less or more water) and can thus be transported to a different geographical location to mitigate nutrient pollution (e.g., from nutrient-rich to nutrient-deficient regions)

Techno-Economic Analysis

Techno-economic analysis was conducted to evaluate the investment and operational costs of each technology pathway in Table 1. The first step in TEA is to construct a general mass balance (product transformation relationships) based on the LCA model and literature data and it is provided in Table S3 and S4. The investment cost of each technology pathway mainly involves the cost of corresponding equipment, and the operational cost mainly involves utility and maintenance costs. Both of those costs are estimated by scaling from data reported based on the mass balance. We note that the purpose of this section is to obtain estimated costs within reasonable orders of magnitude instead of accurate cost analysis. We provide a brief overview below, and readers can refer to the supporting information for more details on the TEA methodology.

Manure needs to be collected first before being processed, and a standard manure collection cost, 0.3 USD/cow/day is applied to all pathways. Collected manure can be stored and land applied (pathway 2 and 7). The investment cost of storage systems includes a fixed construction cost and a proportional cost (related to storage volume). For storage systems with cover, a fixed average additional covering cost is applied.[41] The stored manure retains more than 99% of its original weight, and the loss is mainly due to the emission of gas and evaporation.

Sand recovery systems are needed before AD to adjust the solid content by diluting the manure and increase the stream weight. Due to the limited cost data of the sand recovery system, we assume that both investment and operational costs are proportional to the processing amount (facility size).[42] The sand-recovered manure can be used for AD; AD converts manure into digestate and biogas, and in this analysis, generated biogas is converted to electricity by a generator. The investment cost of the digester is obtained using the so-called 6/10 power-law regression to capture the economies of scale.[43] The investment cost of the electricity generator is set as 2/3 of the corresponding digester (typical estimate used in the literature[43,44]). The operational cost of the AD system includes maintenance cost (which represents 10% of investment) and biogas cleaning cost, which is proportional to the amount of biogas generated. The investment and operational cost of solid-liquid separation equipment (screw press) is obtained from the literature,[45] and the cost of UF/RO technology is obtained from a real-life operation system at a dairy facility in the U.S.

Supply Chain Model

We developed an SC model that aims to systematically make decisions on which technologies to deploy and at which location. The model also makes decision on transport of products (e.g., raw manure) and derived products (e.g., recovered nutrients) between geographical locations. In other words, the SC can be seen as a cooperative system that can exchange products across farms in order to minimize costs and mitigate environmental impacts.

The SC optimization model used is extended from[46] by integrating multiple economic and environmental metrics; this allows us to evaluate the performance of the SC from multiple perspectives.

In the SC model, we have a set of geographical nodes (locations), a set of materials, and a set of technologies (technology pathways). Materials can be transported between geographical nodes and transformed in technologies, and technologies can be installed in certain geographical nodes. The main constraints in the optimization model include material balances and conversion constraints at each location, operational capacity constraints, and logical constraints for technology selection and placement.

The SC model also calculates the *total* (system-wide) TEA and LCA metrics for the entire SC. These metrics contain impacts associated with technology pathways and transportation operations. The decision variables of the SC model include product transport flows and technology selection and placement. The decision variables are a combination of continuous (e.g., flows) and discrete (e.g., selection) variables; the SC model is thus a mixed-integer optimization problem. By adjusting the decision variables, the SC model seeks to minimize the TEA and LCA metrics simultaneously. In other words, the SC problem has multiple objectives that need to be minimized simultaneously. The SC model explored in this work yields large-scale optimization problems that are computationally expensive to solve (a single instance can take hours); for more details, the readers can refer to the supporting information.

Conflict Analysis and Resolution

To facilitate the discussion, we denote the collection of decision variables of the SC model as $\mathbf{x}$, and the system-wide TEA and LCA metrics as $f_1(\mathbf{x}), f_2(\mathbf{x}), \cdots, f_k(\mathbf{x})$, where $k = |\mathcal{I}| + 1$. We further denote the feasible set of the SC model as $\mathcal{X}$, which is defined by the constraints (S15)-(S29).

The economic and environmental metrics considered can be conflicting (decreasing one increases the other). Such conflicts (trade-offs) can be addressed using multiobjective optimization techniques. These techniques traditionally aim to compute the so-called Pareto front (PF); this front contains all solutions that cannot be improved (in the sense that one can not further improve an objective without sacrificing another objective). The PF enables visualization of trade-offs between different metrics (but this is difficult when more than three metrics are explored). A final decision is often selected from the PF based on expert knowledge or preferences by a decision-maker. This choice can be ambiguous because it relies on the priorities of the decision-maker (what metrics are prioritized). Moreover, to obtain the entire PF, it is necessary to solve an extremely large number of optimization problems (e.g., by putting different weights or budgets on the different metrics). For instance, in the multi-stage ϵ-constraint method,[47] one solves the following set of problems:

$$\begin{aligned} \min\ & f_i(\mathbf{x}) \\ \mathbf{x} & \in \mathcal{X} \\ f_j(\mathbf{x}) & \leq \epsilon_j, j = 1, 2, \cdots, k \text{ and } j \neq i \end{aligned} \tag{1}$$

Here, ϵ_j is some pre-defined threshold for objective $f_j(\mathbf{x})$. This method is not computationally feasible in our context because computing a single point on the PF requires solving the entire SC problem, and the number of points needed to describe the complete PF grows exponentially as the number of metrics increases. Sampling strategies are also often necessary to capture points on different regions of the PF, which can require additional computational time. Evolutionary algorithms have also been proposed to reduce the computational complexity, such as NSGA-II and MOPSO method.[48,49] These algorithms do not guarantee optimality and they are not suitable for solving large-scale problems.[50]

An alternative (and more tractable) approach to selecting a solution from the PF is to use a conflict resolution framework. Here, we use a technique known as the utopia-tracking method, which aims to find a solution that balances all the metrics.[51,52] The main idea is to identify the best possible value of each metric to obtain what is known as the utopia point. In most cases, the utopia point is not achievable (non-reachable) since there are inherent conflicts between the different metrics. Instead, this approach aims to find a solution along the PF that is closest to the utopia point; this decision is known as the optimal compromise solution (OCS).

The first step in the utopia-tracking method is to determine the best possible performance of each metric by solving the k problems indicated by equation (2). The optimal objective values for those problems are denoted as $f_1^*, f_2^*, \cdots, f_k^*$, and the combination of them (i.e., $[f_1^*, f_2^*, \cdots, f_k^*]$) is called the utopia point.

$$\begin{aligned} &\min f_i(\mathbf{x}), i = 1, 2, \cdots, k \\ &\mathbf{x} \in \mathcal{X} \end{aligned} \tag{2}$$

Metrics typically have different scales (e.g., different physical units), which makes it difficult to minimize the distance to the utopia point. As such, it is important to scale the metrics properly; this is done by finding the maximum values for the metrics on the PF (i.e., Nadir points). For problems with more than a couple of metrics, the Nadir point can be approximated by using a pay-off matrix:[53]

$$P = \begin{bmatrix} f_1^* & f_{12} & \cdots & f_{1k} \\ f_{21} & f_2^* & \cdots & f_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ f_{k1} & f_{k2} & \cdots & f_k^* \end{bmatrix} \tag{3}$$

In the pay-off matrix P, the diagonal elements are the metric values obtained from (2), and the off-diagonal elements f_{ij} are the objective values of the following problems (4) (i.e., to optimize over a secondary objective while keeping the primary objective at its optimal value). This procedure for constructing the pay-off matrix P is known as lexicographic optimization.[54] The pay-off matrix provides also valuable information on the inherent trade-offs between the objectives.

$$\begin{aligned} &\min f_j(\mathbf{x}), j = 1, 2, \cdots, k \text{ and } j \neq i \\ &\mathbf{x} \in \mathcal{X} \\ &f_i(\mathbf{x}) = f_i^* \end{aligned} \tag{4}$$

The worst possible values of objective $f_i(\mathbf{x})$ on the PF, denoted as f_i^N, are approximated by taking the largest value in the pay-off matrix, as indicated by equation (5), where $\left[f_1^N, f_2^N, \cdots, f_k^N\right]$ denote the approximated Nadir points.

$$f_i^N = \max\left\{f_{i1}, f_{i2}, \cdots, f_{ik}\right\} \tag{5}$$

With this information, we can define scaled metrics, denoted as $\mathbf{o} = [o_1, o_2, \cdots, o_k]$, with elements defined in (6). It is clear that, in the scaled space, all metrics are larger than (or equal to) zero, and on the PF, the metrics are lower than one. In addition, the utopia point in the scaled space is the origin $(0, 0)$. Therefore, the OCS $\mathbf{x}^{OC}$ minimizes the distance to the origin in the scaled objective space, as indicated in (7); here, $\|\cdot\|_p$ represents the p-norm used in distance calculation. If the Manhattan norm is applied ($p = 1$), the problem defined in (7) is linear; while if the Euclidean norm is applied ($p = 2$), the problem becomes quadratic (we chose linear for simplicity). We further denote the objective values of the optimal compromise solution as $\mathbf{f}^{OC} = [f_1^{OC}, f_2^{OC}, \cdots, f_k^{OC}]$

$$o_i = \frac{f_i - f_i^*}{f_i^N - f_i^*} \tag{6}$$

$$\mathbf{x}^{OC} = \arg\min \|\mathbf{o}\|_p \tag{7}$$

The overall conflict resolution procedure is illustrated in Figure 1. This approach consists of the utopia point computation, pay-off matrix computation, and OCS computation. The procedure is illustrated graphically in Figure 2 for a setting with a couple of metrics. The overall procedure needs to solve the entire SC model a total of $k^2 + 1$ times; each of these instances is a mixed-integer linear programming (MILP) problem. In the case study considered here, the entire procedure can take weeks to complete. This highlights the complexity involved in systematically assessing trade-offs in manure management.

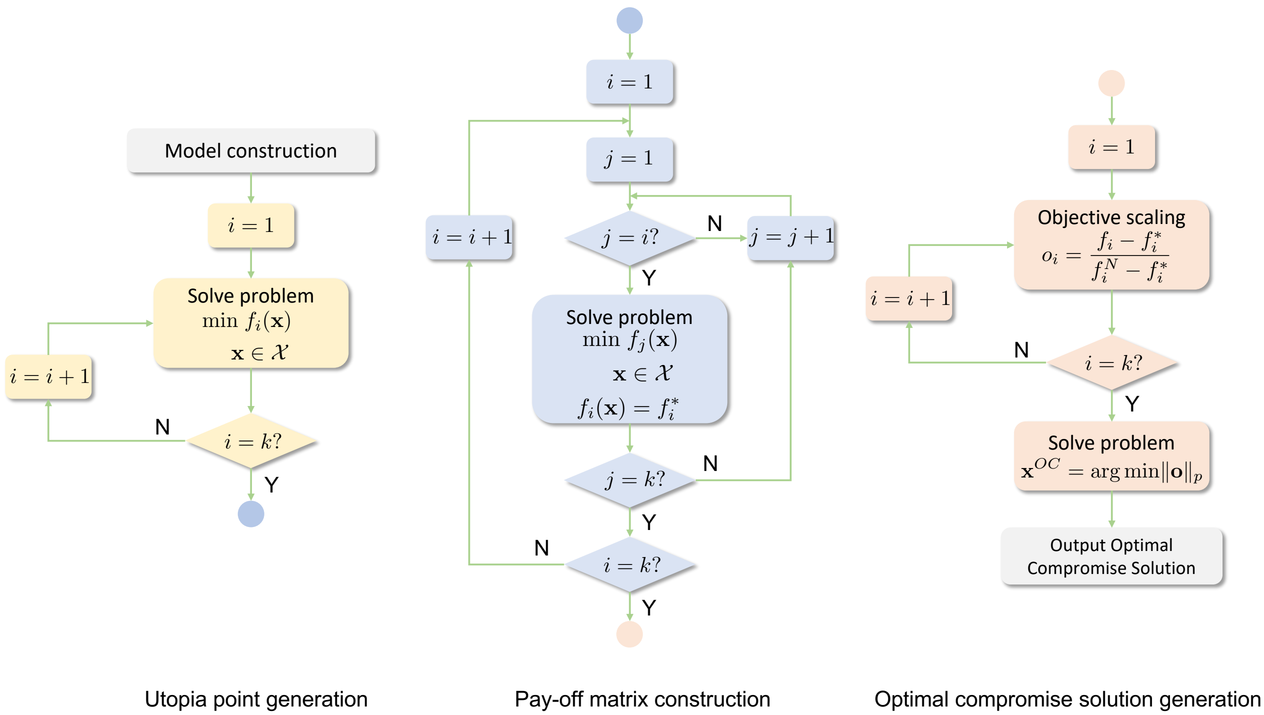

Figure 1: Decision-making procedure using the utopia-tracking method

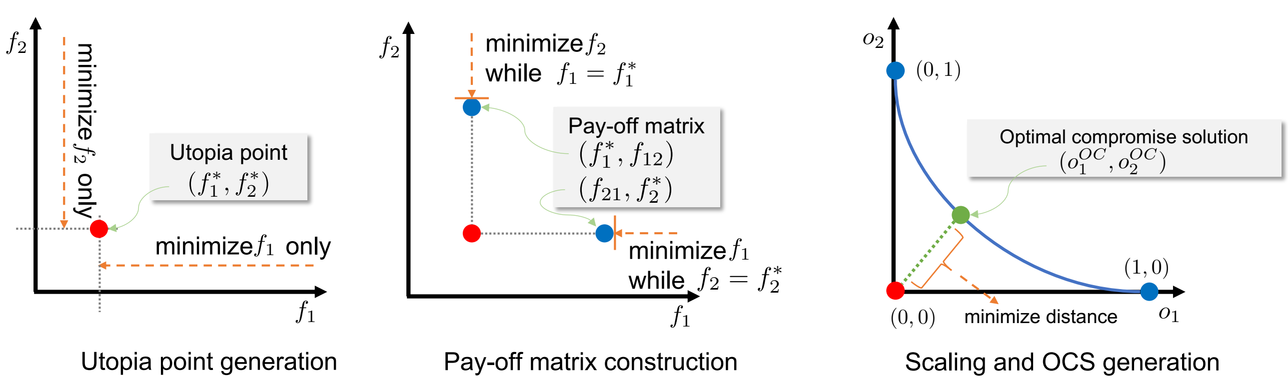

Figure 2: Illustration of utopia-tracking method for problems with two objectives.

Case Study

In this section, we demonstrate the applicability of the proposed computational framework by targeting a case study in Wisconsin.

Study Region: Upper Yahara Watershed

The map in Figure 3 shows the geographical location and boundary of the study region, as well as the location of croplands and farms (beef and dairy). The Upper Yahara Watershed (Lake Mendota basin) has been used as a case study to evaluate the impact of manure storage,[55] manure pelletization,[56] and nutrient recovery technologies.[57,58]

The study region is affected by nutrient pollution due to intensified agricultural activities; the Dane County has made continuous efforts to reduce nutrient pollution (especially P loading) to improve water quality in the lakes (e.g., nutrient pollution leads to HABs). To highlight the degree of nutrient pollution in the region, we define the nutrient balance index (NBI) as the ratio of nutrient applied to land to the amount of nutrient that is removed by crops. This implies that when NBI is greater than one, the nutrient will accumulate in the region and potentially create nutrient pollution issues while, when NBI is less than one, it indicates that there is a nutrient deficiency in the soil (overall soil fertility may be declining and therefore is not sustainable in the long-run). The NBI value for P in the Upper Yahara Watershed in 2012 and 2013, was estimated to be 1.95 and 1.35, respectively.[58] This means that this region has a significant P imbalance.

Previous studies have found that, to reduce P loading and HABs, the most effective strategies are manure storage (shift land application time), manure transportation (shift location for land application), and solid-liquid separation (concentrate nutrients for improved transportation). Unfortunately, these strategies can have a negative impact on other environmental metrics. For example, fossil fuels are consumed in the transport and processing of manure; in addition, manure storage leads to significant CH_4 emissions[38] (due to the anaerobic environment created when liquid and slurry manure are stored). Moreover, the

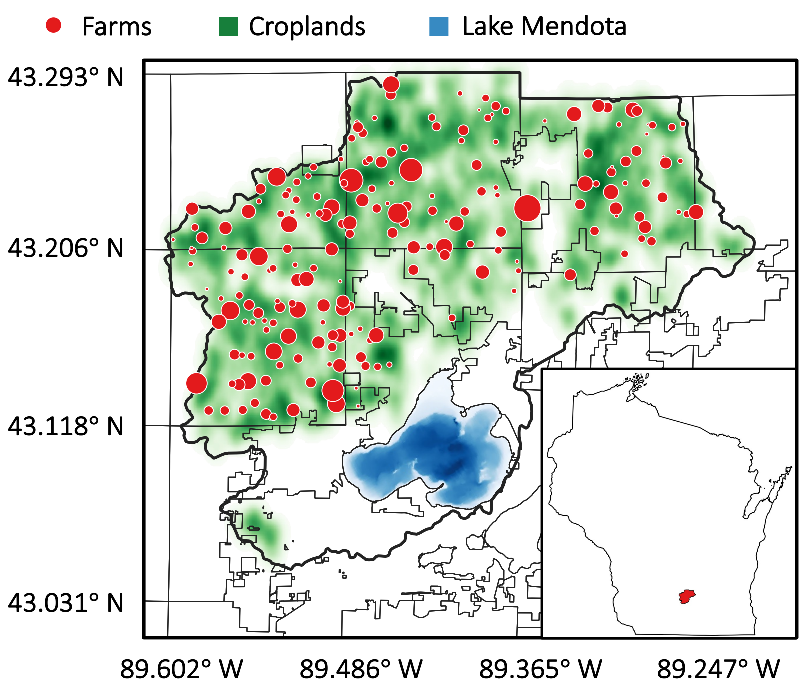

Figure 3: Geographical boundary and agricultural activities in Upper Yahara Watershed: red circles are farms with the size representing amount of manure produced annually, and green areas represent croplands with dark green representing high cropland density

crops considered in the region have different nutrient demand levels. If we consider all the key nutrients for crop growth, such as N and potassium (K), we estimated the NBI for N, P, and K to be 1.27, 1.65, and 1.47, respectively (in 2017). We thus have that all nutrients are imbalanced; although P is the main nutrient that causes nutrient pollution in inland waterbodies, it has been reported that N contributes to nutrient pollution in groundwater.[59] In addition, up to 70% of the excreted N in manure can be emitted as NH_3 in livestock operations.[3] These losses represent 80-90% of the global anthropogenic NH_3 emissions[60] that can redeposit and lead to impaired waterways,[61] or further transform to particulate matter or N_2O. As a result, animal agriculture farmers, researchers, and policy makers need to be aware of current emission levels to target future mitigation strategies. A suitable technology deployment solution should thus take all these metrics and conflicts into account and enable a more comprehensive decision-making process. The data and setting of the supply chain system in this study region is given in supporting information.

Scenario Description

For the baseline scenario (Scenario 1), we only include prevalent technology pathways (technology 1-10 in Table 1) and we study the UF/RO pathway separately. All value-added products (such as electricity) are sold directly under current market prices (without any subsidies from the government). The conflict resolution procedure described in Figure 1 is followed to compute the OCS. Because we have a total of 7 metrics, we need to solve 7 MILP problems to find the utopia point, 42 MILP problems to construct the pay-off matrix, and one additional MILP to obtain the OCS. This gives a total of 50 MILP problems.

We note that, with the specified study area and corresponding data, each SC model is a large-scale MILP problem. For example, a typical model contains 2,548,727 continuous variables, 9,280 binary variables, and 313,699 linear constraints. The SC models were implemented using the Julia-based modeling framework `JuMP` (Version 0.21.2) and were solved with `Gurobi` (Version 9.0.3). The models are computationally challenging; solving the entire set of 50 MILPs require weeks to complete. This illustrate the complexity involved in resolving conflicts in complex SCs such as those arising in manure management. Some of the problems were not solved to optimality within the imposed 35-hour time limit. The time limit is set to balance the trade-off between the solution quality and data storage issues coming from large branching of MILPs. In such cases, the best solution found (usually with an optimality gap less than 10%) is used for analysis. We note that these suboptimal solutions are close to the potential optimal ones and will not impact our main analysis and conclusions.

In Scenario 2, we introduce an UF/RO technology pathway to produce clean water from manure (technology 11 in Table 1) and determine the impact of this technology on the LCA and TEA metrics. Scenario 3 considers prevalent technologies with subsidies introduced into the SC in the form of energy credits (i.e., the system will obtain additional profits when it recovers renewable energy from livestock manure). For Scenarios 2 and 3, the same conflict resolution procedure is followed to analyze how external factors can manipulate the OCS and provide insights to policy-makers and stakeholders. Scenario 3 is included in the supporting information due to space limit.

Results and Discussion

Base Scenario: Payoff Matrix and Optimal Compromise Solution

Table 2 presents the pay-off matrix for Scenario 1. Here, the utopia point consists of the diagonal elements (highlighted as *), and the nadir point consists of the maximum values of each column (highlighted as $\underline{\cdot}$). We use the notation $M_1 - M_2$ to denote the problem with metric M_1 as the primary objective and metric M_2 as the secondary objective. For example, $Cost - GHG$ represents the problem that keeps the cost at a minimum value and minimizes GHG emissions (row 1 and column 2). The notation $M_1 - M_1$ represent the problem with M_1 as the only objective. In addition, we use the notation $M_1 - *$ to represent the problem whose primary objective is M_1.

Table 2: Pay-off matrix, utopia point, and OCS of Scenario 1

Metric	Cost	GHG	NH_3	DFF	Net N	Net P	Net K
Unit	million USD per year	tonne CO_2-eq per year	tonne NH_3-eq per year	GJ per year	tonne N per year	tonne P per year	tonne K per year
(1) min Cost	**10***	19389	2201	34	2297	262	2008
(2) min GHG	19	**236***	1966	-705	2538	283	2146
(3) min NH_3	12	37911	**494***	39	851	34	1537
(4) min DFF	20	537	2050	**-706***	2153	285	2069
(5) min Net N	22	45669	1940	-112	**149***	< 0.1	1418
(6) min Net P	16	800	669	-697	150	**0***	1400
(7) min Net K	19	9718	1253	-580	208	<0.1	**1400***
min value	10	236	494	-706	149	0	1400
max value	22	45669	2201	39	2538	285	2146
OCS value	22	3776	1322	-670	677	29	1449
scaled value	1.01	0.08	0.49	0.05	0.22	0.10	0.07

The pay-off matrix and utopia point provide useful insights to decision-makers, especially regarding the limit behavior of each metric (best and worst values) and the global conflicts between metrics. For instance, we can see that the total cost conflicts with all other environmental objectives. In other words, it is not profitable to reduce any of the analyzed environmental impacts with traditional technologies. This makes sense, as mitigating environmental impacts requires investment. Within the environmental metrics, the GHG shows a strong conflict with nutrient reductions (especially N and K), but a weak conflict with DFF. Similarly, DFF shows weak conflicts with nutrient and costs and a strong conflict with NH_3. The nutrient metrics (N/P/K) show a weak conflict with one another; this indicates that these metrics can be potentially improved simultaneously. For detailed analysis of subproblems presenting in the payoff matrix, readers can refer to the supporting materials.

As shown by the previous analysis, the system can make extreme or irrational decisions when only one or two metrics are considered (and other metrics are ignored). For example, fully focusing on minimization of GHG emissions might lead to high nutrient pollution. The determination of an OCS seeks to avoid these issues by simultaneously capturing all metrics. The metrics obtained for the OCS for Scenario 1 are presented in Table 2. Here, minimum and maximum values from the payoff matrix are listed, OCS values represent the performance of the corresponding metric in the original units, and the scaled values are obtained from (6), which have a unit of one and represent the relative distance along the certain direction.

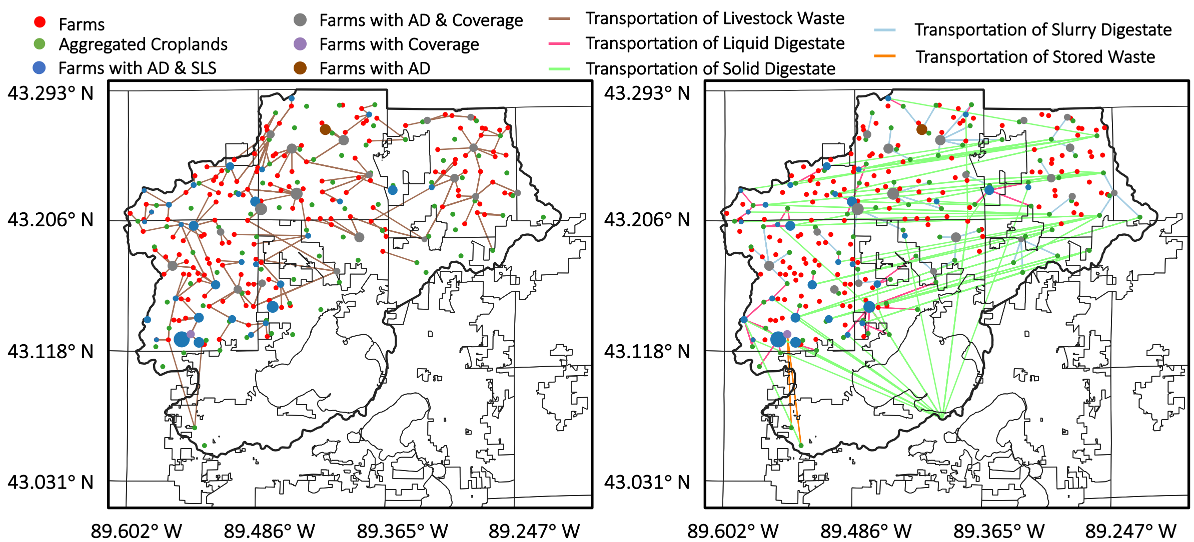

Figure 4: OCS designs for Scenario 1, where left figure shows transportation flows of raw manure, and right figure shows transportation flows of derived products.

The overall cost obtained in the OCS is 22 million USD/year, which is close to the maximum value in the pay-off matrix. This means that, by increasing the cost, the system has economic budget flexibility available to improve all other environmental metrics and can thus resolve the conflicts among those metrics. We can see that the environmental metrics are close to those of the utopia point. The GHG emissions value is 3,776 metric tonnes of CO_2-eq per year. Although this is higher than the utopia value (236 metric tonnes of CO_2-eq per year), it is also an order of magnitude smaller than values obtained with other (e.g., for problems $Cost - GHG$, $Cost - NH_3$, and $Cost - N$). The DFF value is -670 GJ per year, which is only 5% greater than that of the utopia value. A negative value indicates that the SC system produces renewable power that can replace fossil-based grid electricity. The net nutrient release values are 677, 29, and 1,449 metric tonnes per year for N, P, and K, respectively. All of these values are close to the utopia values, but we observe that none of the nutrients is perfectly balanced. We thus see that OCS is seeking to strike a balance between all the objectives.

In the scaled objective space, the distance between OCS and the utopia point is 2.01 (with optimality gap of 12% after 35 hours of solving). Half of the distance is contributed by the cost (1.01), and the rest 6 environmental objectives contribute the remaining distances. This again shows that, for the OCS, the cost needs to be sufficiently large so that the environmental impact can be reduced and then achieve overall smallest distance to the utopia point. Specifically for GHG, DFF, P, and K, all distances contributed by them are less than 0.1.

The SC design under the OCS is shown in Figure 4. To reduce various environmental impacts, the system tends to install different types of processing technologies, including AD, SLS, and covered storage. In other words, the system diversifies investment in other to hit all the metrics involved. There are 31 farms with AD and SLS technologies installed (technology 5, blue dots) and 19 farms with AD and covered storage installed (technology 9, grey dots). There is one farm with ADs (brown dot) and one farm with covered storage (purple dot). We also found that most technologies are installed at medium or large farms, with an average farm size of 590 AU. There are also 23 farms directly sending the raw manure to nearby lands, most of which are small farms and the unprocessed manure only occupies 2.5% of all manure in the study region. The average transportation distance of raw manure, digestate, solid products, and liquid products are 1.93 km, 2.12 km, 15.95 km, and 1.60 km, respectively. Additionally, there is a mix of surface application and injection application used in croplands. Around 41.4% of manure in the system is applied by injection. Due to the mineralization of organic N after the digestion process, using a cover in storage is not sufficient to effectively prevent NH_3 emissions and needs to be coupled with injection as a method for land application. Manure injection can reduce the NH_3 emissions of land application by 95%, and reduce the overall NH_3 emissions by 45%. However, injection increases GHG emissions by 10% consistently with results presented by Chadwick et al.[62] as it creates the necessary conditions to convert nitrate to N_2O. Therefore, the mixed land application method is a technology pathway that seeks to resolve the inherent conflict between GHG and NH_3 emissions.

To summarize, in Scenario 1, most manure is processed by technologies, where 96.9% is processed by AD, 52% is processed by SLS, and 45.4% is stored with coverage. Among those technologies, AD can create benefits in GHG and DFF reduction, SLS can further provide flexibility in product transportation and reduce nutrient losses, and covered storage systems are preferred for decreasing NH_3 and DFF. The average technology sizes are 600 AU, 530 AU, and 680 AU, respectively. These technologies contributes 65.5% to the system cost and 89.4% to the overall GHG emissions, while transportation contributes 34.5% and 10.6% to these metrics, respectively.

Impact of New Technologies

In Scenario 2, the UF/RO technology pathway (technology 11) is added into the system. This technology can provide high efficiency in nutrient separation to obtain clean water (but requires higher investment and operational costs). The centrifuge separator produces solids with high nutrient content (around 30% more concentrated than screw press). The UF and RO byproduct streams are assumed to be used as a liquid digestate products in the SC, and can be directly applied on cropland. The UFC and ROC streams have a lower total solids content than the liquid digestate in this system, as a centrifuge, with higher separation efficiencies, is considered for the clean water separation system vs a screw press for the AD system (Table S2). As a result, it is less economic to transport UFC and ROC due to their larger water content. Clean water is approximately one third of the initial digestate volume and can be directly discharged or consumed by animals (reducing transportation costs). The pay-off matrix obtained under Scenario 2 is presented in Table 3.

The treatment of manure to clean water mainly influences they way nutrients are processed and does not interfere with other metrics (the technologies in Scenario 1 are still selected). As a result, values for cost, GHG, NH3 and DFF metrics are similar to those of Scenario 1. This also indicates that a specific technology reducing an environmental metric in Scenario 1 will also achieve such effect in Scenario 2. With this in mind, even if we consider

Table 3: Pay-off matrix, utopia point, and OCS of Scenario 2

Metric	Cost	GHG	NH_3	DFF	Net N	Net P	Net K
Unit	million USD per year	tonne CO_2-eq per year	tonne NH_3-eq per year	GJ per year	tonne N per year	tonne P per year	tonne K per year
(1) min Cost	**10***	19389	2201	34	2297	262	2008
(2) min GHG	19	**236***	1966	-705	2538	283	2146
(3) min NH_3	12	37911	**494***	39	851	34	1537
(4) min DFF	21	537.4	2050	**-706***	2087	274	1995
(5) min Net N	28	40669	2009	-163	**3***	0	1182
(6) min Net P	13	800	577	-697	3	**0***	1166
(7) min Net K	27	9318	1518	-474	54	0	**1166***
min value	10	236	494	-706	3	0	1166
max value	28	40662	2278	39	2538	283	2146
OCS value	25	4935	1175	-657	563	0	1201
scaled value	0.83	0.12	0.40	0.07	0.22	0	0.33

nutrient as a secondary objective, only transportation can be adjusted and the new UF/RO technology will not be selected (resulting in similar values in the pay-off matrix). After the treatment of manure to clean water technology is installed, N and K are still not balanced, but minimum nutrient release values are achieved due to higher nutrient concentration in the demanded solids; this increases the overall system cost by 28.9% and 43.5%, respectively. Introducing the new technology only brings additional degrees of freedom to balance P, as this was already balanced in Scenario 1. Therefore, some of the problems corresponding to P minimization in Scenario 2 show better performance than Scenario 1. Both problem $N - P$ and $K - P$ are perfectly P balanced, and problems $P - *$ also shows lower NH_3 emissions and DFF consumption. This indicates that the new technology provides flexibility to balance nutrients. For detailed analysis, readers can refer to the supporting information.

The OCS of Scenario 2 was estimated by using the conflict resolution procedure; the results are shown in Table 3. The cost of the OCS is increased by around 3 million USD/year compared with Scenario 1, mainly due to the installment of new technologies. The net N and K releases are reduced by 16.1% and 17.3%, respectively, and P can be perfectly balanced. On the other hand, the GHG and DFF values are increased slightly, mainly due to the decreased biogas production. Generally, the new technology makes nutrient recovery easier and endows the ability to achieve lower nutrient release. If we look at the scaled objective space, the new OCS shows a similar composition to Scenario 1, where the cost contributes almost half of the total distance, and all environmental metrics are properly improved with increased investment. While some of the metrics have slightly worse performance, the new OCS moves toward ideal nutrient management, and it is also closer to the utopia point. The scaled distance to the new utopia point is 1.66 (with optimality gap of 14.9% after 35 hours of solving). If we use the minimum and maximum values in Scenario 1 for scaling, the distance is 1.73, which is decreased by 14.3%.

The SC design obtained with the OCS is shown in Figure 5. It is clear that the system installs different types of technologies to balance conflicts between environmental metrics. In total, 53 farms have AD installed and can process 99.2% of manure, 7 of which are accompanied by uncovered storage systems (technology 8), 33 farms have covered storage systems (technology 9), and 13 of which are equipped with SLS (technology 5). The average sizes of the technologies are 350 AU, 510 AU, and 440 AU, respectively. There are four large treatment of manure to clean water technologies (average size of 2050 AU) installed that can process 25.9% of manure in the region. Compared with Scenario 1, where 52% of manure is processed by AD and SLS, the new treatment of manure to clean water technology replaced almost half of the nutrient recovery task. The total amount of unprocessed manure is also decreased from 2.5% to 0.8% under this new setting. The number of AD systems is increased in order to balance out the additional GHG emissions in transporting raw manure to centralized facilities. For this scenario, the average transportation distance of raw manure, digestate, solid products, liquid products, and UFC/ROC are 2.50km, 1.62km, 11.83km, 0.98km, and 2.50km, respectively. The transportation, investment, and operational cost is increased by 12.6%, 14.4%, and 6.2%, respectively. The additional technology cost are mainly introduced by the UF/RO technologies used. The transportation cost is increased because more manure in the system is processed and also because the more concentrated solid is sold to external customers and the system needs to move diluted streams to balance nutrients in the region.

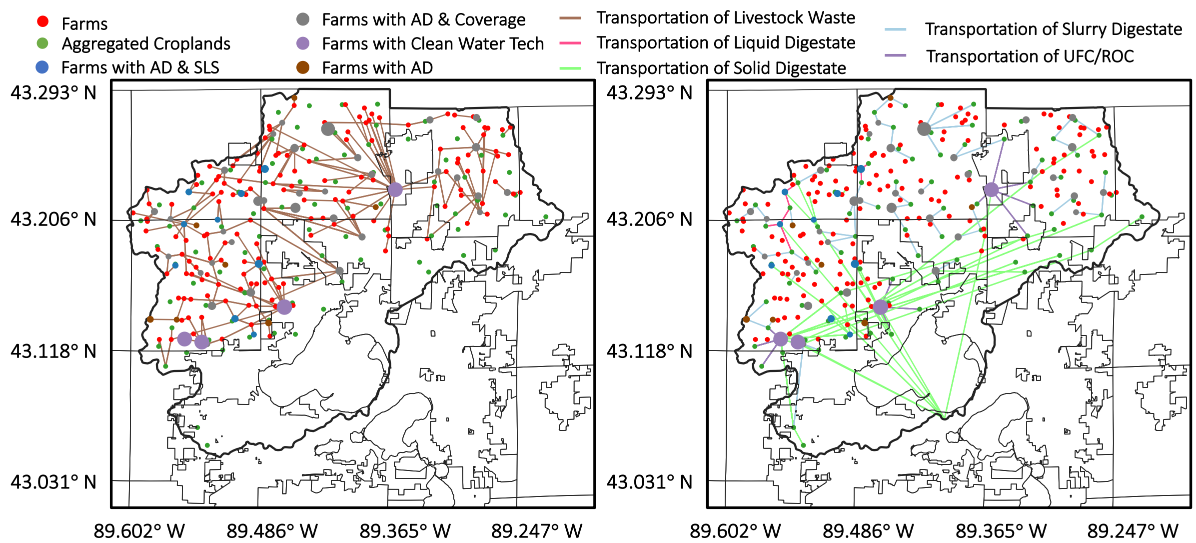

Figure 5: OCS designs for Scenario 2, where left figure shows transportation flows of raw manure, and right figure shows transportation flows of derived products.

Conclusions and Future Work

We presented a computational framework that uses techno-economic analysis and life-cycle assessment to evaluate diverse economic and environmental impacts of manure processing technologies. These impacts are captured in a multi-objective supply chain optimization problem that makes decisions on technology selection/placement and product transportation. The framework also incorporates a conflict analysis and resolution procedure to systematically navigate trade-offs and resolve conflicts. We applied this framework in a case study of Upper Yahara Watershed in the State of Wisconsin. The pay-off matrix generated indicates that the system will not process any manure if the system aims to minimize cost (because land application is the least expensive option). We also found that there are strong conflicts between cost and environmental metrics (GHG emissions, NH_3 emissions, and nutrient emissions). We also found that phosphorus can be balanced more easily in the region than nitrogen and potassium. Some complex conflicts between environmental metrics are also revealed in the pay-off matrix (such as GHG emissions and nutrient emissions and GHG emissions and NH_3 emissions). The optimal compromise solution obtained shows that, to achieve the closes solution to the utopia point, the system cost needs to be increased significantly (the system needs economic budget flexibility) so that other environmental metrics can be improved together. The decisions obtained also involve a mixed use of different technologies (anaerobic digestion and solid-liquid separation) and strategies regarding storage, transportation, and land application to improve environmental metrics efficiently. We also tested the impact of novel technologies and incentives on the optimal comprise solution. We found that the treatment of manure using wastewater purification technologies is able to replace most solid-liquid separation technologies in the optimal compromise solution (despite of its relatively high costs) due to its better separation efficiency. We also found that renewable energy incentives are not able to improve the environmental metrics of the system, but they can mitigate the conflict between GHG emissions and cost. The optimal compromise solution also shows that the system can generate a profit, with slight changes of environmental metrics.

For future work, we plan to further improve the metric selection process. In our current analysis of livestock manure management, the type of environmental metrics included are mainly derived from expert knowledge. While these metrics generally represent the most important aspects in the system, from the perspective of optimization, some of those metrics can be correlated because of their complex interactions. Therefore, some mechanism for prior selection of metrics could be beneficial. We will also seek to understand the potential barriers of deploying optimal compromise decisions in those systems. Our results show that some incentives might only improve economic performance (and not environmental outcomes); as such, we will use our methodology to investigate incentive strategies that can displace the entire set of metrics (e.g., nutrient credits and carbon taxes). We are also interested in identifying optimal compromise solutions for pre-defined economic budgets (as those are typically of interest to stakeholders); obtaining such types of solutions will require a significant amount of computation. We are also interested in investigating algorithms to handle the high computational complexity of the problems under study (which currently take weeks to solve). Finally, we are interested in developing a software tool by integrating the computational framework, so that it can support policy-makers in decision-making of farm operations at a systems level. We envision it could help identify proper technologies and waste processing strategies to best resolve the conflicts between economic and environmental metrics in a specified study region.

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Supporting Information

The Supporting Information is available free of charge at xxx.

Details on life cycle assessment methods; details on techno-economic analysis; mathematical modeling of supply chain network; supplementary analysis on scenario 1 and 2; description of an additional scenario; supply chain design figures

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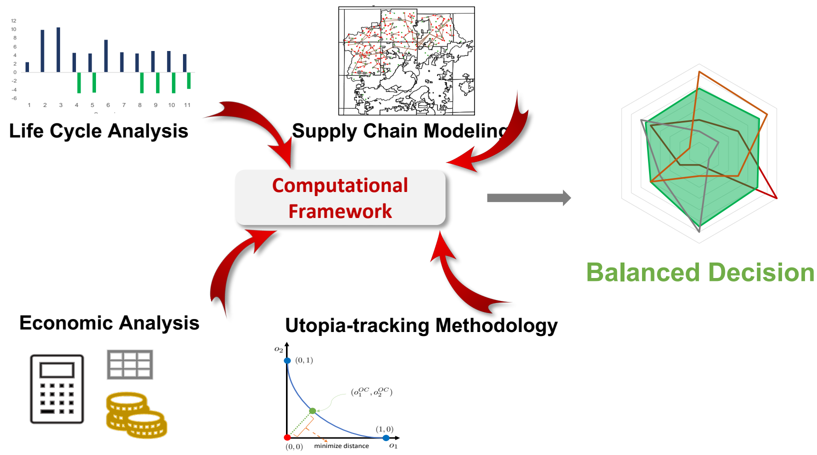

Figure 6: Table of Contents

We proposed a framework for resolving economic and environmental conflicts in dairy waste management by integrating life cycle analysis, economic analysis, supply chain modeling, and a utopia-tracking methodology.