Spatial optimization of nutrient recovery from dairy farms to support economically viable load reductions in the Chesapeake Bay Watershed

Femeena, P. V.[1]; Costello, C.[2]; Brennan, R. A.[1]

[1]The Pennsylvania State University, Department of Civil and Environmental Engineering, 212 Sackett Building, University Park, PA 16802

[2]The Pennsylvania State University, Department of Agricultural and Biological Engineering, 105 Agricultural Engineering Building, University Park, PA 16802

[*]Corresponding author (rab44@psu.edu)

ABSTRACT

CONTEXT. To promote circularity in agricultural systems, the utilization of aquatic vegetation for ecological wastewater treatment is a potential mechanism to capture and upcycle nutrients. Agricultural wastewater is an excellent growing medium for aquatic plants like duckweed, offering opportunities for wastewater treatment and conversion of harvested biomass into bio-based products, including protein-rich livestock feed, which can potentially replace conventional soil-based crops such as alfalfa.

OBJECTIVE. We hypothesize that nitrogen (N) and phosphorus (P) loadings to the Chesapeake Bay Watershed (CBW) can be reduced via replacing alfalfa cultivation with manure-grown duckweed by: a) reducing excess manure application on agricultural fields; b) reducing synthetic fertilizer application on alfalfa croplands; and c) decreasing the release of fixed N back into the environment from the decomposition of alfalfa crop residue.

METHODS. This study developed an optimization framework to identify locations where alfalfa-to-duckweed replacement could be theoretically employed to minimize N and P loads into the CBW. A relative effectiveness (RE) indicator representing landscape-specific nutrient delivery capacity was included within the framework. Using county-level data on alfalfa yields, cropping area, and nutrient inputs from alfalfa croplands and dairy manure, we identified alfalfa cultivation areas that could be removed and replaced with full or partial duckweed cultivation and land conservation for optimal benefits.

RESULTS AND CONCLUSIONS. At the county scale, counties in Pennsylvania (especially Lancaster and adjacent regions) with widespread farming operations and high RE values consistently indicated the greatest benefit by replacing large areas of alfalfa cultivation (> 80% in each county) with duckweed. Using nutrient load minimization as the primary objective function, a 2.9% N reduction and 2.4% P reduction can be achieved at the watershed scale by converting only 7.6% of the total alfalfa cropland area into duckweed farms. Upon introducing production cost minimization as a competing second objective function, up to 12.8% N reduction and 9.2% P reduction are possible with a 40% decrease in the alfalfa cropping area. A 10-year economic analysis demonstrated the possibility for superior return on investment with this approach, leading to almost seven times the baseline net revenue with alfalfa production, primarily attributed to the higher protein content and corresponding revenue potential of duckweed.

SIGNIFICANCE. Many different constraints on alfalfa production (ex., maintaining some baseline production) and duckweed replacement strategies (ex., utilization of decommissioned alfalfa area vs. soil conservation) were used in this study, which offer a wide range of optimal solutions that consider both environmental and economic tradeoffs.

Keywords: Optimization; duckweed; dairy manure; alfalfa; nutrient recycling; circular bioeconomy

1. INTRODUCTION

Excessive concentrations of nutrients in the Chesapeake Bay Watershed (CBW) have long been known to cause eutrophication and hypoxia, leading to declining ecosystem health in the bay region (Russell et al., 2008). According to the Chesapeake Bay Foundation (CBF, http://www.cbf.org), agricultural activities contribute to the largest share of nitrogen (N) and phosphorus (P) loads reaching the Bay, of which 17% N and 38% P are attributed to manure, and 15% N and 28% P are attributed to fertilizers (CBF, 2010; Majsztrik & Lea-Cox, 2013). Dairy operations alone amount to 20% of manure P and 24% of manure N generated within the watershed (Devereux, 2009). State and federal initiatives are being steered to achieve the total maximum daily load (TMDL) targets set by the U.S. Environmental Protection Agency for all the bay watershed segments (USEPA, 2010). However, most restoration efforts have been focused on point-source nutrient load reductions, and the EPA does not have the authority to enforce a permitting process to curb non-point source pollution such as that coming from manure- and fertilizer-laden runoff (Hinkle, 2021).

Alfalfa is considered one of the highest-quality forages, and dairy cows efficiently utilize its protein (13-18% on a dry matter basis), calcium, and fiber for producing milk (Jennings, 2005). Many dairy farmers located in the CBW's nutrient hotspot regions such as Lancaster, PA, grow their own alfalfa as protein feed for their cows. To unload the excess dairy manure generated in these regions, farmers typically carry out manure spreading on their farms. Since synthetic fertilizers generally are also applied to these fields, this practice leaves a substantial amount of nutrients in the soil that may leach as runoff and subsurface flow. Therefore, proper manure and fertilizer management are vital in addressing the issue of degraded water quality in watersheds with intensive dairy operations such as the CBW. A more sustainable solution for attaining water quality benefits could consist of a circular system that efficiently utilizes the excess manure and simultaneously upcycles the waste nutrients to produce animal feed without using additional fertilizers.

With the simultaneous increase in meat and milk production to feed the growing human population (Ritchie & Roser, 2017) and the rising trend of plant-based diets, there is a high demand to find alternative non-animal protein sources for both feed and food. Duckweed (a small floating aquatic plant of the Lemnaceae family) is emerging as a potential candidate for sustainable protein production (Roman et al., 2021). Duckweed can proliferate under a wide range of environmental conditions and accumulate up to 45% protein by dry mass (Leng, 1999). Its ability to uptake nutrients when grown in agricultural wastewater has been exploited in the past as a promising way to promote circular agricultural systems (Adhikari et al., 2015; Iqbal, 2012; Timmerman & Hoving, 2016). Duckweed produced in this way can not only be used as animal feed, but also as a biofuel feedstock (Calicioglu et al., 2021; Pena et al., 2017; Zhao et al., 2015), fertilizer-substitute (Fernandez Pulido et al., 2021; Kreider et al., 2019), and potential human protein source (Roman et al., 2021). On dairy farms, duckweed offers an excellent pathway to convert manure nutrients into valuable feed and other by-products through cultivation on diluted manure. Substituting alfalfa feed with manure-grown duckweed may help alleviate the problems arising from nutrient pollution in surrounding water bodies by reducing the field application of manure and fertilizers. Converting low-yielding marginal lands to duckweed farms could further provide additional economic benefits to farmers and alleviate feed scarcity.

Due to the widely varying land use and biophysical characteristics in the CBW, it is essential to take a spatially targeted management approach to reduce the nutrient loads delivered to the Bay. Hotspot regions comprising dairy farms and alfalfa cropping areas present ideal locations to implement manure-based duckweed cultivation as a substitute for the existing alfalfa feed production. In this study, we present a watershed-scale spatial optimization framework that identifies CBW counties for optimal manure-based duckweed cultivation in order to minimize N and P loads generated in the watershed. Specifically, we focus on reducing the transport and delivery of nutrients contained in dairy manure and alfalfa fertilizers by finding critical counties where existing alfalfa farms can be replaced with duckweed farms. Since duckweed cultivation comes with a high capital cost and return on investment compared to row crops such as alfalfa, the economic tradeoffs of growing duckweed on dairy farms have also been incorporated into the optimization framework.

Overall, we evaluated the economic feasibility and environmental benefits of replacing alfalfa production on dairy farms with duckweed cultivation by: 1) finding optimal manure-based duckweed production areas at a county-scale that would minimize nutrient loads entering the Chesapeake Bay; and 2) assessing spatial patterns of optimized duckweed cultivation scenarios involving constraints for both alfalfa production and economics.

2. METHODOLOGY

2.1. Study area and data

The Chesapeake Bay is an estuarine system with a drainage area spanning 166,000 km^2 across the entire District of Columbia (DC) and parts of Pennsylvania (PA), Delaware (DE), Virginia (VA), West Virginia (WV), and New York (NY). The primary land cover in the watershed is forest (54.5%), followed by pasture (14.9%), developed areas (10.8%), and cultivated crops (9.5%) (Kang & Sridhar, 2018). The watershed consists of 203 counties, of which 118 have dairy farms. Lancaster and Franklin counties in PA together account for approximately 30% of the dairy cows within the CBW (Figure 1).

County areas were extracted from the U.S. Department of Agriculture National Agricultural Statistic Service (USDA-NASS) database (https://www.nass.usda.gov/). The remaining variables used in the study were obtained from a Commodity-Specific Net Anthropogenic Phosphorus and Nitrogen Inputs (CSNAPNI) model that estimates county and watershed scale N and P nutrient inputs to crop and animal products ((Algren et al., 2021, 2022); https://github.com/malgren/CSNAPNI). Several modifications are currently being made to the CSNAPNI model to increase the spatial resolution and incorporate region-specific fertilizer rates. However, the latest available version (as of July 2022) was adopted for the current study. The results from the CSNAPNI model used here are: (1) alfalfa production; (2) N and P in fertilizers applied to alfalfa; (3) N in soil from atmospheric fixation; and (4) N and P in recoverable manure, all at county-scale (in tons per year). Here, the N and P values are the gross anthropogenic inputs to the land and do not account for losses due to transport and other biogeochemical processes. The model uses a yield-based approach to estimate agricultural N fixation, which for alfalfa is assumed to be 0.031 kg N/kg dry matter (Han & Allan, 2008; Hong et al., 2013). Recoverable manure corresponds to the amount of manure that is collectible and available for land application (Kellogg et al., 2011). ArcGIS tools were utilized to clip the counties that intersected the CBW boundary, and proportional ratios were applied to determine the value of all variables in the clipped county areas (Eq. 1).

$$X_{clipped} = X_{county} * \frac{A_{clipped}}{A_{county}} \tag{1}$$

where A_{county} is the total county area, X_{county} is the actual variable value for the county, $A_{clipped}$ is the clipped area inside the watershed boundary, and $X_{clipped}$ is the value of the variable corresponding to the clipped area. The distribution of the number of dairy cows and alfalfa production on a county-scale are shown in Figure 1.

To account for the effect of geographical characteristics on the amount of nutrients delivered to the Bay, relative effectiveness (RE) values of N and P established by the Chesapeake Bay Program watershed model were used (https://www.chesapeakebay.net/; Chesapeake Bay Program (2020); Figure 2). These indicators are calculated by combining riverine and estuarine effectiveness that estimates the improvement in dissolved oxygen per pound of nutrient reduction to the local river. In other words, they aid in the targeted implementation of nutrient management practices by identifying regions with higher RE values where interventions would most effectively improve the Bay's water quality. Since the effectiveness is estimated for 1,902 land-river segments that are smaller in scale than the county-scale used in our study, area-weighted averaging was used to calculate the RE for each county. Although RE values exist separately for two types of sources (wastewater treatment plants and all other sources), we used the values corresponding to 'all other sources' to represent a broader range of non-point source nutrient pollution contributors.

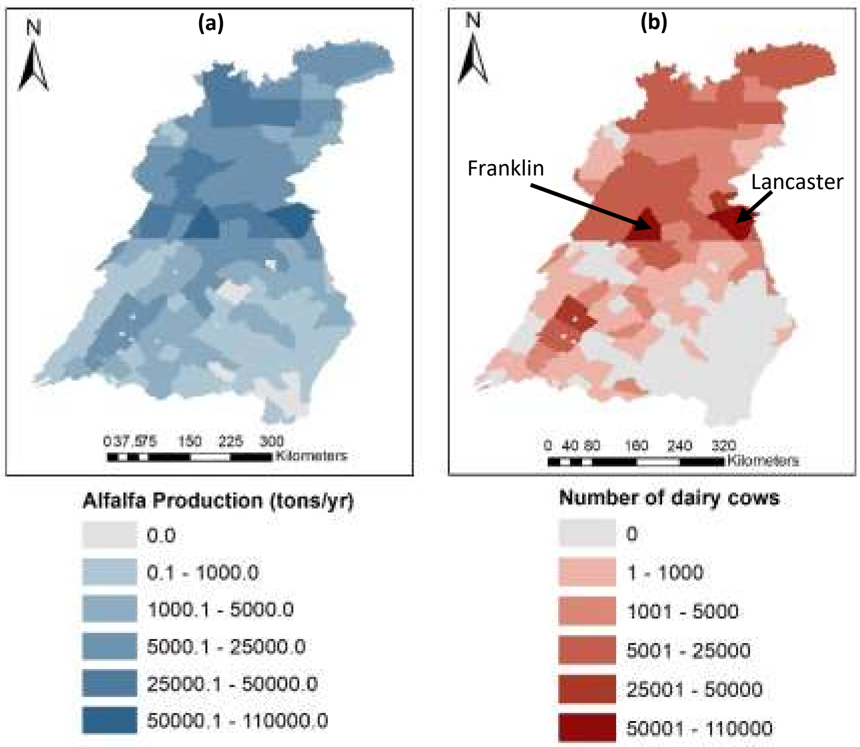

Figure 1. County-level spatial distribution of (a) alfalfa production and (b) the number of dairy cows in the Chesapeake Bay Watershed showing hotspot counties (Lancaster and Franklin) with the highest alfalfa and dairy manure production.

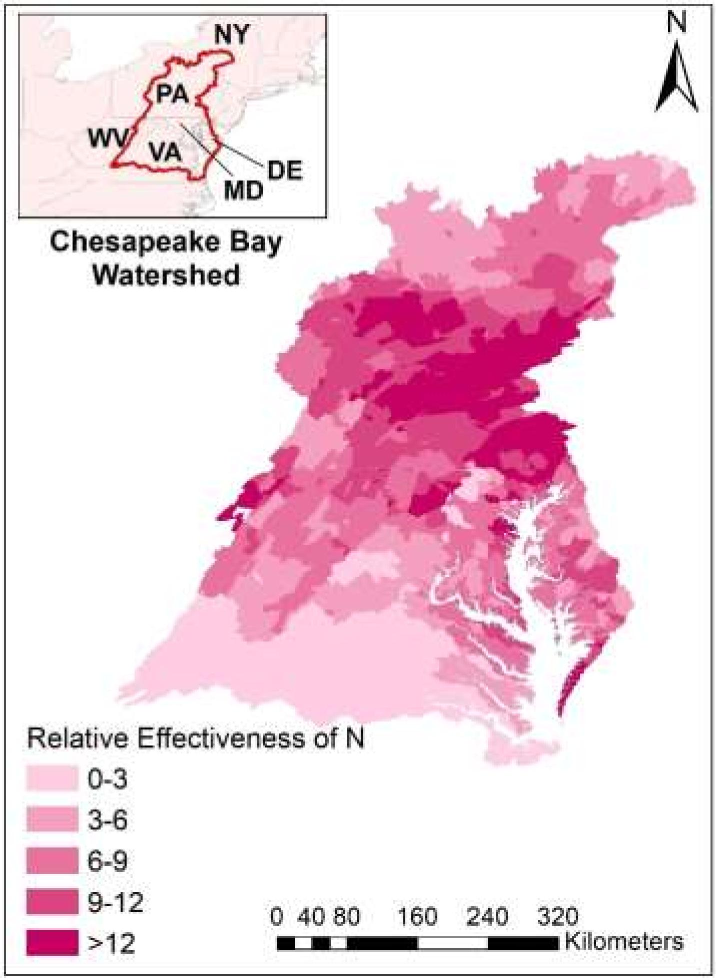

Figure 2. Location map of the Chesapeake Bay watershed showing the relative effectiveness of nitrogen delivery for all land-river segments (adapted from *(Chesapeake Bay Program, 2020)***.**

2.2.AMALGAM Optimization

A Multi Algorithm Genetically Adaptive Method (AMALGAM) developed by (Vrugt & Robinson, 2007) was used in this study to perform the spatial optimization of duckweed cultivation locations. AMALGAM runs four different optimization algorithms in parallel (Non-dominated Sorted Genetic Algorithm (NSGA) II, particle swarm optimization, adaptive metropolis search, and differential evolution) and allows information sharing between these algorithms to produce the best optimal solution. Studies in the past have demonstrated the effectiveness of using

AMALGAM in model calibrations and spatial optimization frameworks (Cibin & Chaubey, 2015; P. V. Femeena et al., 2018; Liu et al., 2016). It merges the strengths of different algorithms, which when used independently, may lead to widely varying optimal solutions depending on factors such as initial parameter values. Combining algorithms in this manner has been shown to yield superior and more convergent results compared to single-algorithm techniques (Zhang et al., 2008).

The optimizing variable was the percentage of alfalfa cropping area removed in each county that has dairy production (118 counties in total). Inside the optimizer, these values (between 0 to 100%) were randomly generated and provided as input to the module that calculates the objective function value for each iteration. The objective functions used for the different scenarios are described in Section 2.2.1. A population size of 100 was assumed for this study, which means that for each iteration, the optimizer generates 100 randomly generated parameter values. As the iterations progress, the algorithms narrow down the search region of parameter values based on objective function values from previous iterations and finally converge to parameter sets with minimum objective function values (Figure 3). All optimization runs had a termination criterion of 100,000 iterations – a high value selected to ensure that the optimization yields reasonable convergence of objective function values.

The scenarios were run on a MATLAB programming platform, with script files consisting of AMALGAM algorithms and additional modules to compute our user-defined objective functions. Within the objective function module, replacing the land removed in alfalfa with duckweed followed two different kinds of substitution strategies depending on the chosen scenario: a) Growing duckweed on all of the land removed from alfalfa production, resulting in higher protein production than the baseline scenario (since duckweed has more protein content than alfalfa); or b) Growing duckweed on only part of the land removed from alfalfa to produce an equivalent amount of protein as the baseline scenario, and leaving the remaining land uncultivated. Both strategies could reduce the fertilizer application and fixed N in the soil due to the reduced area of alfalfa land under cultivation and simultaneously decrease the manure runoff from farms by utilizing it for duckweed production. The rationale behind selecting these two strategies is that they provide different types of benefits to the farmers and the environment. Strategy 'a', with its larger share of land under duckweed production, will have greater nutrient load reduction benefits when compared to strategy 'b'. However, strategy 'b' would be a better choice if agricultural land retirement (as a soil conservation measure) is a priority and socio-economic barriers in transitioning all of their farmland to a new crop are of concern to farmers. Across the study, we assume that the total area of land made available for duckweed cultivation is entirely used to construct outdoor ponds for growing duckweed. Since the entire area available in each county could be far greater than a typical pond size, a reasonable assumption involves spatially distributed ponds covering the total area. Vertical duckweed farming, which can generate higher yields with a lower land footprint than conventional ponds, is another potential growth system not considered in this study.

The equations below illustrate the computational steps used to estimate the new duckweed area and the resulting nutrient and manure load reductions for a certain percentage of the land area removed from alfalfa production (all values calculated at the county-scale). Eq.s (2) and (3) correspond to duckweed area calculations using the two substitution strategies described above.

Strategy 'a' (land conversion of all removed alfalfa to duckweed)

$$DW_{area} = \frac{\%\, alfalfa\ area\ removed * Alf_{area}}{100} \tag{2}$$

where DW_{area} = new duckweed area and Alf_{area} = existing alfalfa area

Strategy 'b' (equivalent baseline protein production)

$$DW_{area} = \frac{\%\, alfalfa\ area\ removed * Alf_{area}}{100} * \frac{Alf_{yield} * Alf_{protein}}{DW_{yield} * DW_{protein}} \tag{3}$$

where DW_{area} = new duckweed area; Alf_{area} = existing alfalfa area; Alf_{yield} = average alfalfa yield (27.7 dry ton/ha/yr, (Penn State Extension, 2019)); DW_{yield} = average duckweed yield (30 dry ton/ha/yr, (Leng et al., 1995)); $Alf_{protein}$ = average protein content of alfalfa (15%, (Foster et al., 2009)); and $DW_{protein}$ = average protein content of duckweed (35%, (Leng et al., 1995)). Note that the duckweed yield used here is an optimistic estimate based on a review conducted by Leng et al. (1995) that looked at yields from growing duckweed under real-world conditions (reported range = 10 to 30 tons/ha/yr).

Once the new county areas under duckweed and alfalfa production were computed, nutrient loads corresponding to alfalfa production were determined by simple proportional relationships (Eq. (4)).

$$Nutr_{new} = Nutr_{existing} * \frac{A_{new}}{A_{existing}} \tag{4}$$

where $Nutr_{new}$ is the new nutrient load (N fertilizer, P fertilizer, or N fixed), $Nutr_{existing}$ is the existing nutrient load, and A_{new} and $A_{existing}$ are the new and existing areas under alfalfa.

Manure loads from each county were estimated assuming a 13 gal/day/animal-unit of dairy manure production (Penn State Extension, 2017) and using an average value of 1.5 animal units per dairy cow. The N and P contents in liquid manure were assumed to be 24 lb/1000 gal (2875.8 mg/L) and 9 lb/1000 gal (1078.4 mg/L), respectively (Jokela & Peters, 2009). Since raw manure is extremely high in nutrients, it cannot be used directly for growing duckweed. A previous study demonstrated that duckweed growth is optimal when the N concentration in the media is 60 mg/L

(P. V. Femeena et al., 2022). Accordingly, a 2.1% manure dilution was considered, and the remaining manure was counted towards the total manure that gets land applied and delivered to the Bay. The sum of N (from fertilizer, fixation, and manure) and P (from fertilizer and manure) at the county-level were multiplied by the corresponding RE values of each county to estimate the effective N and P loads delivered to the Chesapeake Bay. For the final objective functions, watershed-scale nutrient loads were computed, as discussed in Section 2.2.1. When two objective functions (for nutrients and cost) are considered simultaneously, the optimizer tends to minimize the objective function with the higher order value. To eliminate this bias, scaling factors were used to convert the actual objective function values to a smaller order index values.

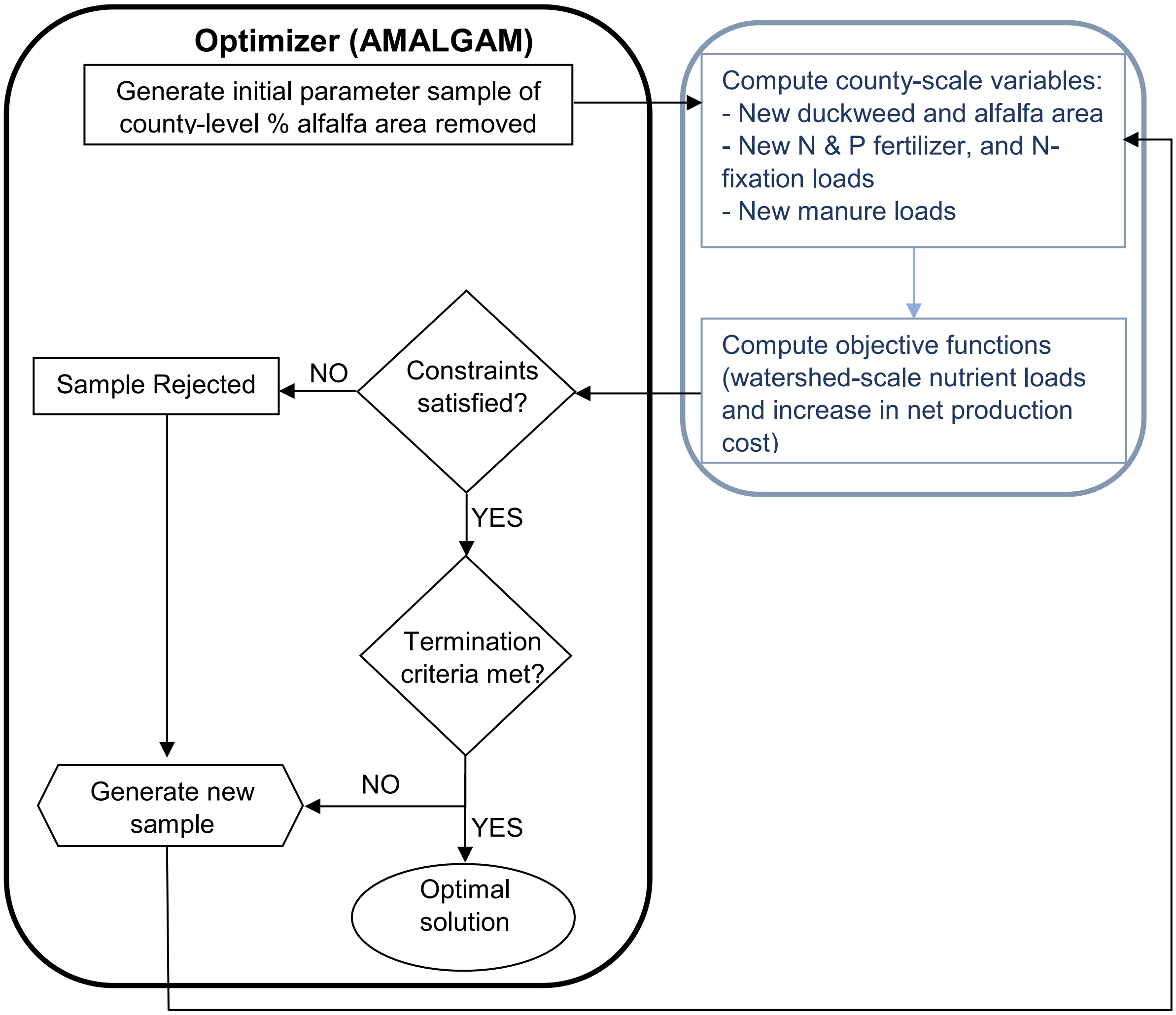

Figure 3. Flowchart outlining optimization framework utilizing AMALGAM algorithm (method adopted from Femeena et al. (2018)).

2.2.1. Scenario Selection

In addition to the baseline (existing) scenario, eight additional scenarios were formulated to evaluate the effect of alfalfa-to-duckweed farm conversion on watershed-scale nutrient loads and production cost (Table 1). The primary differences in the scenarios are: 1) the type of objective function used (single objective to reduce nutrient loads or two objectives to reduce nutrients and cost of production); 2) duckweed replacement strategy (baseline equivalent protein production or conversion of all removed alfalfa area to duckweed cultivation). An added constraint was necessary for an effective optimization run for the single objective scenarios (1-6). This is because a single-objective optimization for nutrient reduction without any competing constraints would result in the most optimal scenario of 100% conversion of alfalfa to duckweed in all counties, which is unrealistic. We formulated hypothetical cases where a certain percentage of the total baseline alfalfa cropland area has to be retained. For instance, scenario 1 ensures that 90% of the baseline alfalfa cropland area is maintained or that only 10% of the alfalfa land is available for duckweed cultivation. This analysis also considered two additional cases with 70% and 50% alfalfa production constraints. A constraint on baseline production ensures that the impact on existing farming systems is not very high, avoids market fluctuations, and reduces socio-economic burdens on farmers who are hesitant in transitioning to newer crop varieties.

Table 1. Scenarios used in the optimization runs and their corresponding objectives, constraints, and duckweed replacement strategy used.

Scenario	Objective(s)	Constraint	Duckweed Replacement Strategy
1	Minimize nutrients	90% baseline total watershed alfalfa cropland area	All removed land cultivated with duckweed
2		70% baseline total watershed alfalfa cropland area	
3		50% baseline total watershed alfalfa cropland area	
4	Minimize nutrients	90% baseline total watershed alfalfa cropland area	Baseline protein production maintained; Remaining land left uncultivated
5		70% baseline total watershed alfalfa cropland area	
6		50% baseline total watershed alfalfa cropland area	

7	Minimize nutrients and cost	-	All removed land cultivated with duckweed
8			Baseline protein production maintained; Remaining land left uncultivated

2.2.1.1 Single objective optimization

The objective function (OF) for scenarios 1-6 involves minimizing total watershed nutrient loads from the Chesapeake Bay (Eq. (5)). The effective N and P loads from all counties are summed and divided by a factor of 10^6 to scale it down to a smaller value, referred to here as the 'Nutrient load index (NLI)'. It should be noted that the variables used in Eq. (5) correspond to tons of N and P, which are typically not added together in real-world conditions. In addition, since the nutrient loads are multiplied with RE values (that range from 0 to 25), OF1 does not have a physical meaning. In other words, it does not indicate the actual load value for the watershed but rather implies an index representative of the relative amount of nutrient loads reaching the Bay.

$$OF1 = \frac{\sum_{i=1}^{203}(Alf_{Ni}+Manure_{Ni})*RE_{Ni}+\sum_{i=1}^{203}(Alf_{Pi}+Manure_{Pi})*RE_{Pi}}{10^6} \quad (5)$$

where: OF1 is the objective function (also called the NLI); i is the county number; Alf_{Ni} and Alf_{Pi} are the N and P from alfalfa croplands (through fertilizers/soil fixation); $Manure_{Ni}$ and $Manure_{Pi}$ are the N and P from dairy manure; and RE_{Ni} and RE_{Pi} are the relative effectiveness values for N and P, averaged for each county.

The baseline alfalfa production constraints (90%, 70%, and 50%) were incorporated into the algorithm by setting OF1 to a very large value (10^6) if the watershed-level alfalfa production exceeds 90%, 70%, or 50% of the baseline production, respectively. Since the algorithm is automatically designed to minimize the value of OF1, this approach will force the optimizer to eliminate parameter search in the region that produces high OF1 values. The final parameter set at the end of 100,000 runs was selected as the optimal solution.

2.2.1.2 Two-objective optimization

Duckweed production involves a high capital cost in the first year due to construction costs associated with building ponds and setting up storage and drying facilities for the harvested duckweed. Therefore, it is essential to consider the economic tradeoffs associated with converting existing alfalfa farms to duckweed cultivation systems. For scenarios 7 and 8, a cost-based objective function (Eq. (6)), also called the 'Net cost index (NCI)', was thus introduced in addition to OF1 described in Eq. (5). Specifically, OF2 was set to minimize the increase in annual net cost compared to the baseline scenario. The first summation term in the numerator in Eq. (6) corresponds to the net cost (production cost – revenue) associated with the new optimized scenario, and the second term is the net cost for the baseline scenario.

$$OF2 = \frac{\sum_{i=1}^{203}[(AlfCost_{new} - AlfRev_{new}) + (DWCost_{new} - DWRev_{new})] + \sum_{i=1}^{203}[AlfCost_{Base} - AlfRev_{Base}]}{10^8} \quad (6)$$

where: OF2 is the second objective function (also called the NCI); i is the county number; $AlfCost_{new}$ and $AlfRev_{new}$ are the annual alfalfa production costs and revenue for the new scenario; DW$Cost_{new}$ and $DWRev_{new}$ are the annual duckweed production costs and revenue for the new scenario; $AlfCost_{Base}$ and $AlfRev_{Base}$ are the annual alfalfa production costs and revenue for the baseline scenario.

For estimating the annual costs and revenue, the following assumptions were made (all values presented on an annual basis): Alfalfa production cost = $45.34 per ton (Penn State Extension, 2019); Alfalfa revenue = $229 per ton dry matter assuming a moisture content of 15% (Foster et al., 2009). Duckweed production costs were determined by performing a detailed techno-economic analysis (TEA) involving: 1) capital costs which include the costs for land, pond construction, and drying tent; and 2) operating costs associated with duckweed harvesting and drying (See Supporting Information for cost breakdown and assumptions used in the TEA). The analysis yielded an annual duckweed production cost of $19,847.50 per ha and a revenue of $16,005.16 per ha. This cost corresponded only to year one production and was used in all the two-objective optimization runs. However, for long-term analysis, we used only the operating costs ($4447.89/ha/year) from year two onwards. Revenue from duckweed cultivation was calculated using the same protein feed value as alfalfa and by applying a weighted ratio based on protein percent ($DW_{revenue} = Alfalfa_{revenue} * \frac{DW_{protein\%}}{Alfalfa_{protein\%}}$). Assuming the protein content to be 15% in alfalfa (Foster et al., 2009) and 35% in duckweed (Leng et al., 1995), we estimated a duckweed protein feed value of $535.29 per ton dry matter. We also conducted a long-term (10-year) economic analysis to evaluate and compare the return on investment for alfalfa versus duckweed farming systems.

Since the two-objective optimizations involve competing functions of NLI and NCI, the final solutions for scenarios 7 and 8 are in the shape of a pareto-front that corresponds to multiple optimal parameter sets instead of a single parameter set (as seen in the case of a single-objective optimization). In other words, multiple combinations of OF1 and OF2 can be considered optimal values; therefore, selecting one optimal solution is subjective and dependent on the study goals. For the purpose of this study, three data points (one at each of the extreme ends of the pareto-optimal front and one at the center) were manually selected for further analyses. ArcGIS software was used to spatially visualize the optimal duckweed production patterns in the CBW for each of the eight scenarios. Nutrient load reductions, decreases in alfalfa land area, and increases in first-year net cost and 10-year cumulative net revenue were extracted for comparison across the different scenarios.

3. RESULTS

Spatial analysis of USDA and CSNAPNI model data (Figure 1) revealed that Pennsylvania (PA) counties, which in total constitute 33% of the total CBW area, account for the largest share of recoverable dairy manure (66%) and alfalfa fertilizer loads (65% of N loads and 70% of P loads). The existing baseline scenario results in 44.80 x 10^4 tons of N input (6.5% from alfalfa fertilizers and soil fixation, 93.5% from dairy manure) and 18.39 x 10^4 tons of P input (1.1% from alfalfa fertilizers, 98.9% from dairy manure) generated in the watershed from dairy manure and alfalfa fertilizers alone. Of the three major sources considered, dairy manure dominated the nutrient share (93.5% of the total), whereas the contribution from fertilizers and N fixation was very small (6.5%). Baseline production costs and revenue associated with alfalfa production were estimated to be $46.25 million and $234.02 million, respectively, resulting in net revenue of $187.77 million for the entire watershed.

3.1. Optimization results

3.1.1. Single objective optimization

With nutrient load minimization as the only objective function, the optimizer yielded an optimal parameter set within the first 10,000 runs, with negligible reduction in OF1 beyond the 10,000th iteration. The optimal NLI values were 0.83, 0.73, and 0.65 for 90%, 70%, and 50% baseline alfalfa production constraints in scenarios 1-3 (Figure 4a). This corresponds to N loads of 43.50 x 10^4, 40.84 x 10^4, and 38.56 x 10^4 tons, indicating a reduction of 2.9%, 8.8%, and 13.9% from the baseline, respectively (Table 2 and Figure 5). Similar decreases in P loads were also observed - Scenario 1: 17.94 x 10^4 tons (2.4%), Scenario 2: 17.19 x 10^4 (8.8%), and Scenario 3: 16.53 x 10^4 tons (10.1%).

Although alfalfa only covers 7.6% (1,200 km^2) of the cropland in the CBW, it can potentially export a significant quantity of N from land to the rivers. At an average export rate of 14 kg/ha/yr, the total N exported from alfalfa fields can amount to 1680 tons annually (Shenk & Linker, 2013). The CSNPANI model data used in this study revealed that alfalfa alone contributes to 29,128 tons of N input (as fertilizer and soil-fixed N) and 2,100 tons of P input in the entire watershed; combining the input from recoverable dairy manure, that increases to 76,356 tons of N and 10,733 tons of P, respectively. Results from single-objective optimization indicate that with only 10% of the alfalfa land in the entire watershed allocated for manure-based duckweed cultivation, a total amount of 12,991 tons of N and 4,438 tons of P inputs can be reduced annually. If only part of the removed land is used for duckweed cultivation (while maintaining baseline protein yield), the overall manure treatment capacity is reduced, which results in slightly higher nutrient loads or NLI (Figure 4b). Assuming a protein content of 35% for duckweed and 15% for alfalfa, scenario 3 (with up to 50% alfalfa land available for duckweed cultivation) would yield an extra protein production of 10.31 x 10^5 tons/yr if all of the removed lands are utilized for farming duckweed on dairy manure waste. This is 68% higher than the baseline protein production of 6.14 x 10^5 tons/yr with alfalfa alone. While the difference in optimal NLI between the two types of duckweed replacement strategies is very small, the full alfalfa-to-duckweed conversion strategy results in an additional annual removal of 6,100 tons of N and 2,500 tons of P from the total watershed loads.

The cost analysis showed that the full duckweed-substitution strategy (scenarios 1-3) comes with a higher production cost than the partial duckweed substitution strategy (scenarios 4-6), as expected from the increased capital cost in the first year associated with farming duckweed. While scenarios 1-3 resulted in a 33-185% increase in net cost in the first year, scenarios 4-6 had a comparatively lower increase in cost at 20-103% for the three different constraints considered (Table 2 and Figure 5). By financing the initial production cost over a longer timeframe (typical of most farm equipment investments), farmers could reap long-term profits via duckweed protein sales while avoiding high up-front costs. When a period of 10 years is considered, the returns from protein sales of duckweed compensate for the high capital cost, as exemplified in the cumulative net revenue increase (70-312% for strategy ‘a’ and 35-99% for strategy ‘b’). Replacing all removed alfalfa land with duckweed growing systems is also the optimal scenario for both water quality benefits and long-term profits.

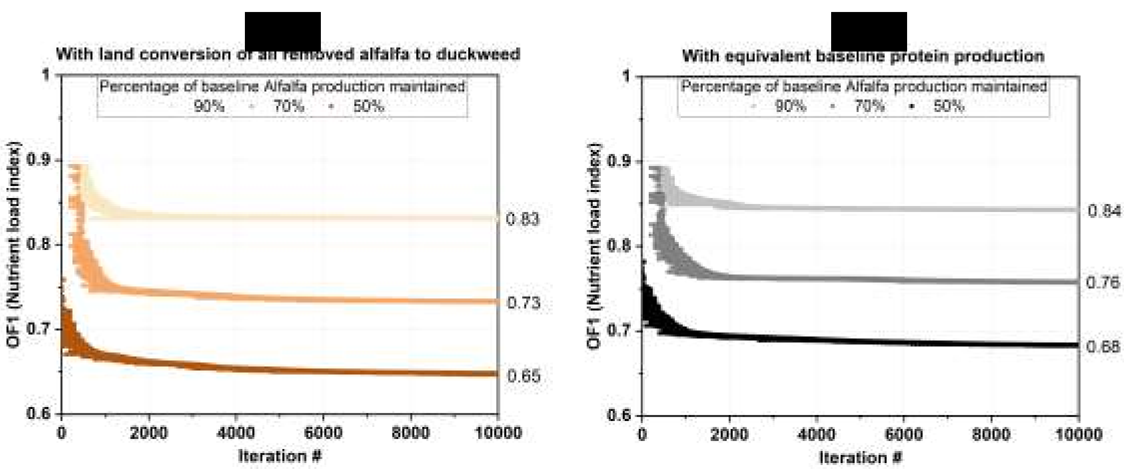

Figure 4. Data points representing each iteration of the single-objective (nutrient minimizing) optimization with different types of duckweed replacement strategies. Panel (a) represents scenarios 1-3 for all removed land-to-duckweed conversion, and (b) represents scenarios 4-6 for equivalent baseline alfalfa production. The data is truncated at 10,000 runs since changes in the optimal values were insignificant beyond that point.

Table 2. Optimization results for the scenarios examined in this study compared to baseline values at the watershed scale.

				Optimal Results			Change from baseline				
Scenario	**Objective(s)**	**Constraint**	**Duckweed replacement strategy**	**Duck-weed area (ha)**	**N load ($x10^4$ tons/yr)**	**P load ($x10^4$ tons/yr)**	**Reduction in alfalfa area (%)**	**N reduction (%)***	**P reduction (%)***	**Increase in net cost in the first year (%)**	**Increase in net revenue after 10 years (%)**
Baseline	-	-	-	0.0	44.8	18.4	0.0	0.0	0.0	-	-
1	Minimize nutrients	90% baseline alfalfa production	All removed alfalfa land to duckweed	11347.5	43.5	17.9	7.7	2.9	2.4	33.2	70.5
2		70% baseline alfalfa production		38831.2	40.8	17.2	26.3	8.8	6.5	109.5	192.7
3		50% baseline alfalfa production		65776.9	38.6	16.5	44.5	13.9	10.1	184.6	312.0
4	Minimize nutrients	90% baseline alfalfa production	Baseline equivalent protein production	4704.7	44.1	18.2	8.1	1.5	1.0	19.6	35.1
5		70% baseline alfalfa production		15169.6	42.7	17.9	25.9	4.6	2.8	61.0	66.5
6		50% baseline alfalfa production		25965.2	41.5	17.6	44.4	7.5	4.3	103.1	99.6
7 (Case A2)	Minimize nutrients and cost	-	All removed alfalfa land to duckweed	59595.3	39.0	16.7	40.3	12.9	9.2	168.2	283.6
8 (Case B2)			Baseline equivalent protein production	20965.7	42.0	17.7	35.9	6.3	3.7	85.1	82.4

**Refers to the percentage reduction in N and P inputs (from fertilizers, N fixation, and dairy manure) for the entire Chesapeake Bay Watershed.*

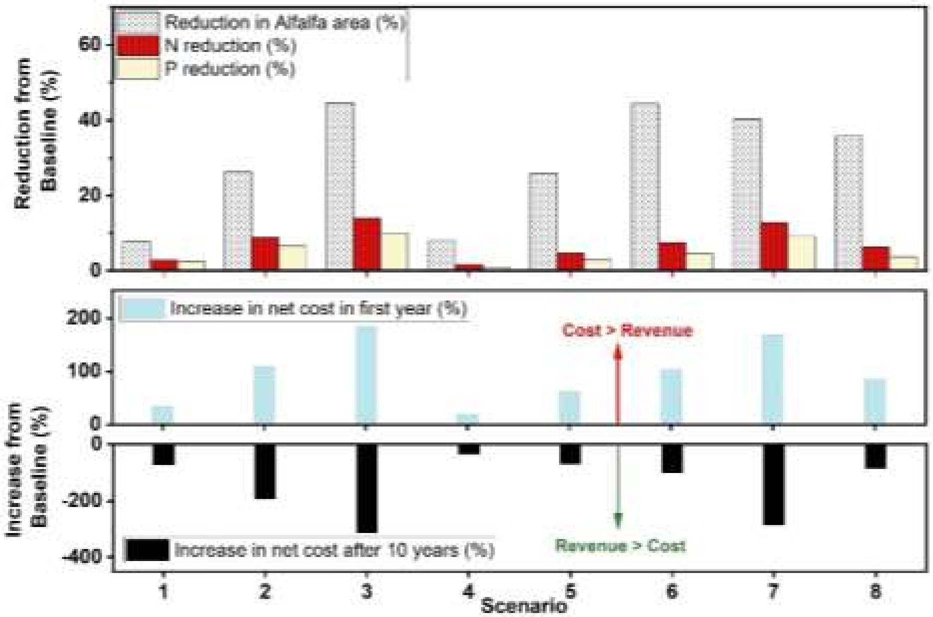

Figure 5. Scenario comparisons showing watershed-level nutrient load reduction, alfalfa area reduction, and increases in first-year net cost and cumulative 10-year net revenue for the eight different optimization scenarios.

3.1.2. Two-objective optimization

With net cost minimization introduced as the second objective function, the solution obtained is in the form of a pareto-optimal front (Figure 6). Since both OF1 and OF2 were to be minimized, all the data points along the pareto-front can be considered as an optimal solution. Three cases were selected along each of the pareto-optimal fronts of scenarios 7 (all removed alfalfa-to-duckweed conversion) and 8 (equivalent baseline protein production): A1, A2, and A3 correspond to the selected cases in scenario 7; and B1, B2, and B3 correspond to those in scenario 8.

Cases A1 and B1, representing the zero cost/maximum nutrient scenarios, are the same as the baseline scenario with zero alfalfa-to-duckweed conversion. Case A3 is the maximum cost scenario which indicates 100% substitution of all removed alfalfa land with duckweed. This scenario also provides the largest environmental benefit with a 23.2% reduction in N and a 19.4%

reduction in P inputs from baseline values. The increase in first-year net cost for this case is considerably high at 386.1% ($724.9 million above the baseline alfalfa production cost across the entire watershed). But it also equates to an elevated increase in protein production (146.5% higher than baseline protein production from alfalfa). In this scenario, the return on investment is extremely high due to the large amount of duckweed produced, and therefore, within the second year, cumulative revenue surpasses the cumulative production cost resulting in high profits.

Case A2 can be considered as the 'true optimal' solution in our study since it occurs towards the center of the pareto front exhibiting a balanced minimum value for both nutrient load and cost (NLI and NCI). With a 12.8% reduction in N load and a 9.2% reduction in P load, case A2 simultaneously comes with an economic drawback: a 168.2% increase in net cost for the first year of duckweed cultivation. This additional cost, however, will be paid back over the 10-year period, showing almost a 4-fold increase in cumulative net revenue at 10 years compared to if the existing alfalfa production scenario were to continue (Table 2 and Figure 5). If economic constraints are not a concern, case A3 represents the most ideal scenario demonstrating double the environmental benefits over the 'optimal' case A2.

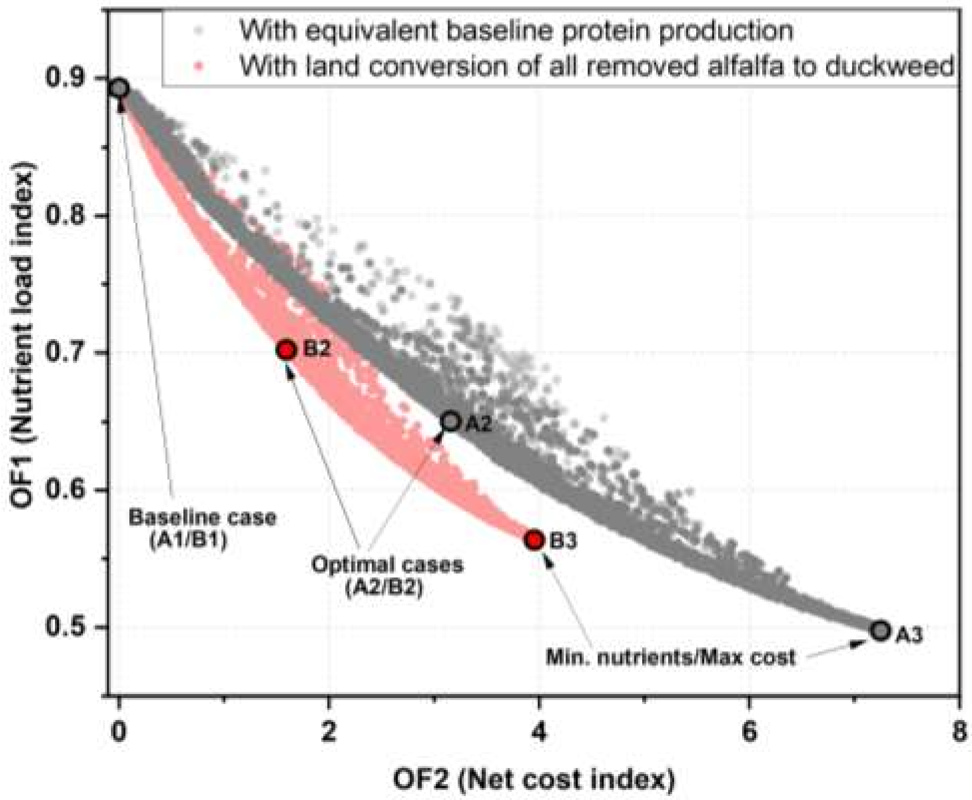

Figure 6. Data points representing each iteration of the two-objective (nutrient and net cost minimizing) optimization with different types of duckweed replacement strategies. The cases highlighted in the figure are the selected points identified for further analysis.

The parameter search region shrank considerably when the duckweed replacement strategy was changed to strategy 'b' with partial duckweed cultivation for equivalent baseline protein production. This is because it acts as a constraint on the optimization where the algorithm is forced to limit the duckweed cultivated area to produce only as much protein as the baseline scenario. Accordingly, case B3, the highest cost case for strategy 'b', is 2.5 times less than the similar high-cost case (A3) in strategy 'a'. In terms of annual reduction in nutrients generated, case B3 decreases N and P loads by 12.9% and 8.3%, respectively, over the baseline. The increase in the first-year net cost to farmers is about 210.7% (compared to 386.1% in case A3), and 10-year cumulative net revenue shows an increase of 3 times over the baseline condition (compared to 7.6 times in case A3). Case B2, considered here as the 'true optimal' case, would decrease the watershed-scale N and P loads by only 6.3% and 3.7%, respectively, which are slightly less than half of what was achieved in the optimal case A2 with the full duckweed conversion strategy (Table 2 and Figure 5). Consequently, the increase in first-year net cost is lower than case A2 (85% compared to the baseline) and the 10-year cumulative net revenue is only 2 times that of the baseline value.

3.2. Spatial patterns of optimal duckweed farming locations

3.2.1. Single objective optimization

As expected from the high RE values and the substantial quantities of dairy manure generation and alfalfa production in PA counties, the largest share of alfalfa-to-duckweed conversion occurs predominantly in PA and other counties in the upper half of the watershed (Figure 7). This is consistent across all the constrained scenarios 1 to 6 (with 90%, 70%, and 50% baseline alfalfa production constraints). For scenarios 1 to 3 with strategy 'a' duckweed replacement (full conversion), the optimized spatial pattern showed a total land conversion of 11,347 ha when 10% of the alfalfa cropland is available for duckweed cultivation compared to 38,831 ha and 65,776 ha when 30% and 50% alfalfa croplands are available, respectively (Table 2). Only 12 counties out of 203 showed more than 10% land conversion from alfalfa to duckweed in scenario 1, indicating that reasonable nutrient reduction (12,991 tons of N and 4,437 tons of P) can be achieved by just targeting the top 6% of the hotspot counties (Figure S1, Supporting Information). For scenarios 2, 3, 5, and 6, which had greater flexibility in land availability for duckweed cultivation, the number of counties that achieved modeling optimization of more than 10% land conversion was in the range of 57 to 75 (less than half of the total number of counties in the watershed).

Lancaster county showed the highest effectiveness in reducing nutrient loads, with 83% conversion in scenario 1 and 100% conversion for scenarios 2 and 3. We obtained similar results for strategy 'b' duckweed replacement (partial conversion), where Lancaster county had 72%, 100%, and 100% land conversions for scenarios 4, 5, and 6, respectively. Equifinality is a known issue in optimization studies with several variables wherein different parameter combinations result in similar results. This may have led to some counties being displayed as hotspots in certain scenarios and not in the rest (for example, Broome county in NY and Adams county in PA being hotspots in all scenarios except 8). However, there were still several counties with a large number of dairy cows and high RE values that could be considered critical in reducing overall nutrients delivered to the Bay, with examples including: Warren and Essex counties in Virginia; Garett county in Maryland; Lebanon, Luzerne, Montour, Mifflin, Juniata, York, Chester, Northumberland, Berks, Columbia, Clinton, Perry, Snyder, and Dauphin counties in PA, which showed recommendations for more than 50% alfalfa land conversion for most of the scenarios studied (Figure 7). Optimal duckweed farming locations revealed similar spatial patterns for the two duckweed replacement strategies considered, indicating that the hotspot counties remain the same whether full or partial duckweed cultivation is utilized. The major difference between the two strategies is the higher mass of potential protein production and greater reduction in nutrient delivery when full alfalfa-to-duckweed conversion is employed as opposed to partial conversion (as discussed in Section 3.1).

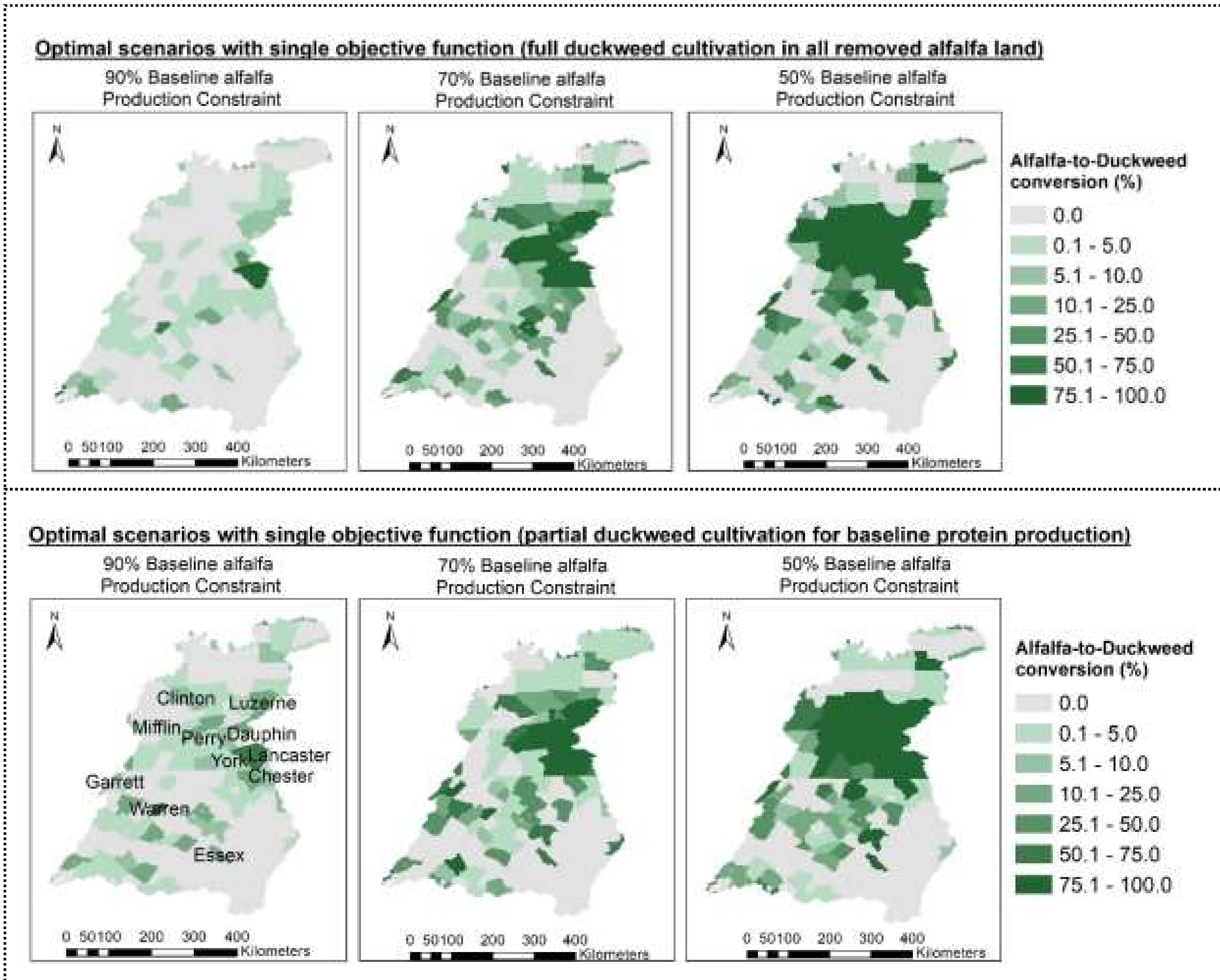

Figure 7. Spatial pattern showing the optimal distribution of land converted from alfalfa to manure-based duckweed cultivation for single-objective (nutrient load minimizing) optimization. Scenarios with two types of duckweed replacement strategies are shown: (a) Scenarios 1 to 3 with full duckweed cultivation in all removed alfalfa land (upper panel); and (b) scenarios 4 to 6 with partial duckweed cultivation to maintain equivalent baseline protein production (lower panel).

3.2.2. Two-objective optimization

Similar to the single-objective optimization, optimal patterns in scenarios 7 and 8 with both nutrients and cost included in the objective functions showed a greater percentage of alfalfa cropland removed from counties mainly in PA and those close to the Bay region (Figure 8). In scenario 7, out of the 24 counties that recommended > 80% land conversion, only three were outside PA: Frederick in MD; Alleghany in VA; and Ontario in NY. A noteworthy observation is that Ontario county in NY and Allegheny county in VA are not dairy-farm-intensive counties and do not appear in the optimal pattern for scenario 8, again highlighting the equifinality problem in optimization problems.

Optimal cases A2 in scenario 7, and B2 in scenario 8, would result in new duckweed cultivation areas of 59,595 ha (40.3% reduction in alfalfa land) and 20,965 ha (35% reduction in alfalfa land), respectively (Table 2). Since A2 utilizes all the removed land for duckweed cultivation, it has higher nutrient reduction benefits (12.8% in N and 9.2% in P) when compared to B2 (6.3% in N and 3.7% in P) and offers additional protein production (3.78 x 10^5 tons more than baseline).

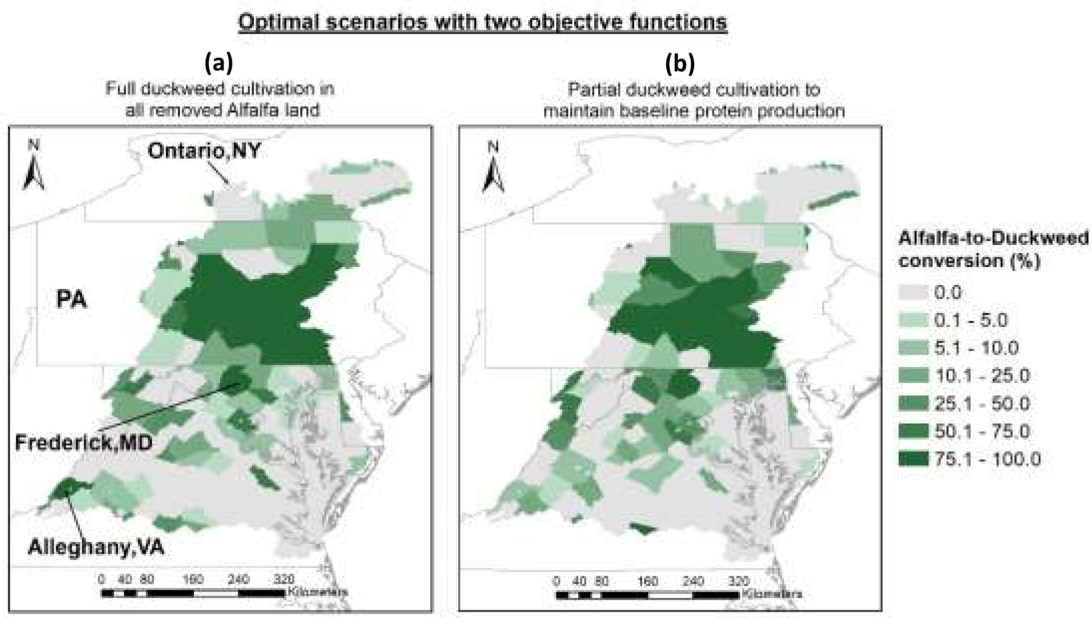

Figure 8. Spatial pattern showing the distribution of land converted from alfalfa to manure-based duckweed cultivation for two-objective optimization (minimizing nutrient load and net cost). Scenarios with two types of duckweed replacement strategies are shown: a) Case A2 in scenario 7 with full duckweed cultivation on all removed alfalfa land (left); and b) Case B2 in scenario 8 with partial duckweed cultivation to maintain equivalent baseline protein production (right).

4. DISCUSSION

The non-linear multi-objective optimization proposed in this study warranted the use of an enhanced evolutionary algorithm, as validated by Toscano et al. (2022). While spatial optimization and land prioritization models have been developed in the past using a host of simple optimization methods such as linear programming (Malczewski, 1999), the more advanced evolutionary algorithms like NSGA tend to produce more accurate results when multiple objectives and constraints are involved (Cao et al., 2011; Wang et al., 2021). Prior CBW-focused work has primarily employed single-objective optimization to identify cost-effective best management practices (BMPs) in the watershed (Z. Kaufman et al., 2014; Talberth et al., 2015). Methods like linear programming and the interior-point method have been used successfully in some of these studies, but these algorithms, albeit faster, often times converge to a local optimum and lead to erroneous solutions (Santos et al., 2003). Although employing a single algorithm for spatial optimization could have decreased the runtime considerably, a combination algorithm was preferable for our study due to the scale, high number of variables, and the complexity of the processes involved (Maringanti et al., 2009). With the AMALGAM framework, we utilized a proven enhanced optimization method that integrated the advantages of different algorithms to improve the sampling process and reduce the computational burden with faster convergence to a global optimum. The results showed successful and quick convergence to create an optimal solution in single-objective optimization (converged in 2000-3000 iterations), and a distinct pareto-optimal front in two-objective optimization (converged in 5000-6000 iterations).

Prior to conducting the optimization runs, Pennsylvania counties such as Lancaster and Franklin, known for their widespread farming operations, could be visually identified as the notable nutrient hotspot regions. In addition, from a geographical and hydrological connectivity perspective, RE values were also higher in PA counties owing to the shorter travel time of nutrients from catchments in this region to the Chesapeake Bay (Figure 2). Results from quantitative analysis suggest that PA is the lead contributor of N and P inputs to the CBW, accounting for 66% of recoverable dairy manure, meriting spatially targeted nutrient management. Similar findings highlighted by several other studies in the CBW support this observation (Devereux, 2009; Kleinman et al., 2012). Considering that in 2017, the Commonwealth of PA failed to meet their agricultural N reduction targets by 36% (EIP, 2017), there is immense value in advancing targeted nutrient management of PA farms.

The major share of dairy manure towards the total N and P generated in the watershed (93.5%) showed that manure storage and management is very crucial in curbing nutrient pollution. Past studies have found that fertilizers are the primary nutrient source in the CBW, accounting for 28-31% of the total watershed load compared to 40-54% from manure (Chesapeake Bay Foundation, 2004). The lower share of nutrients from fertilizer and N fixation (6.5%) compared to manure (93.5%) observed in our study is attributed to the fact we only considered a single crop (alfalfa). Although alfalfa is a nitrogen-fixing crop with lower N fertilizer requirements than other row crops, it needs P fertilizers and a certain amount of supplemental N during the seeding phase (Oregon State Extension, 2020). Hence, there is added benefit in the proposition of utilizing alfalfa lands for manure management and soil conservation through duckweed farming.

4.1. Single Objective Optimization

Ignoring the economic tradeoffs of implementing duckweed cultivation, the results from single-objective optimization revealed that over 10% N and P reductions (at-source) are possible by using 65,777 ha of alfalfa land in the watershed. For context, the U.S. Environmental Protection Agency (USEPA) in 2010 had established a TMDL goal for the Chesapeake Bay that aims to achieve a 25% reduction in N and a 24% reduction in P loads present in the Bay by the year 2025 (USEPA, 2010). A previous modeling study focusing on a sub-watershed (Spring Creek) within the CBW has shown that a 1.7-23% reduction in N and 2.7-30% reduction in P is possible by implementing BMPs such as buffer strip, no-till, cover crop, manure injection, etc. in up to 6000 ha of land (Amin et al., 2020). Another optimization study of the Conewago Creek watershed found that reallocating crop rotations in the ~5500 ha agricultural area could alone lower N and P loads by 15% and 14%, respectively (Jiang et al., 2021). It is important to note that the nutrient loads reported in our study represent the N and P generated at-source and are not directly indicative of the actual nutrients reaching the Bay, which may be lower due to load attenuation during nutrient transport, presence of BMPs, manure processing strategies, etc. But given that around 20-25% of net anthropogenic N inputs and 10% of P inputs are exported to the Bay (Howarth et al., 2006; Najjar et al., 2010; Russell et al., 2008), the relative nutrient reductions quantified here could still be representative of the load reductions possible within the Bay. With duckweed emerging as a potential new feed crop in many countries worldwide (Huque et al., 1996; Sońta et al., 2019; Tanuwiria & Mushawwir, 2020), growing it adjacent to livestock farms could be viewed as an effective BMP in achieving the CBW's nutrient reduction goals.

As per 2012 statistics, PA, VA, and MD have been identified as the largest sources of pollutants in the CBW and are together required to achieve an additional reduction of 172.5 million pounds (78,244 tons) of N by 2025 to meet the Chesapeake Bay Program targets (Majsztrik & Lea-Cox, 2013). As stated earlier, it is not reasonable to directly compare these values to the at-source nutrient inputs reported in our study. However, assuming that 20-25% of anthropogenic N flux ends up at the watershed outlet (Russell et al., 2008), Scenario 6 with the highest land conversion, could in effect reduce N loads reaching the Bay by 12,484-15,605 tons a year. Considering the amount of nutrients that can be recycled through manure-based duckweed systems, it would be an excellent pathway toward achieving the above-mentioned target, especially for the manure hotspot counties in the CBW.

4.2.Two-Objective Optimization

For the two-objective optimization, the most environmentally sustainable scenario was Case A3, which had the most land area under duckweed cultivation and displayed the highest reduction in N and P loads (23.2% in N and 19.4% in P). Even if we account for load attenuation, this can still be crucial in achieving the USEPA TMDL targets on nutrient reduction required in the Bay waters (25% for N and 24% for P; USEPA (2010)). Unfortunately, this scenario is logically almost impossible due to the likely socio-economic barriers in overcoming farmer resistance to adopting alternate crops and infrastructural limitations related to installing new crop-growing systems. The optimal cases A2 and B2 had nutrient reduction benefits ranging from 6.3-12.8% in N and 3.7-9.2% in P. Of these, case A2 (under Scenario 7) utilizes all removed alfalfa land for duckweed production and hence, offers an advantage of additional protein production (61.6% more than baseline), which could benefit farmers economically. An average PA dairy farm purchases a good portion of its protein feed (287 kg/cow/yr) from external sources (Holly et al., 2019). Assuming a duckweed growth rate of 10 g/m^2/day and protein intake of dairy cow to be 11 lbs/cow/day, cultivating duckweed in a 1.4 ha pond for seven months can produce enough protein to feed 100 cows annually (Robinson, 2023; Said et al., 1979). Feed and fertilizer purchases are undeniably a large environmental concern due to their associated carbon footprint and greenhouse gas emissions. Additionally, from a nutrient balance perspective, feed and fertilizer imports are known to decrease the nutrient use efficiency in farms when the imported nutrients are in excess of their removal through crop uptake (Soberon et al., 2015). By allowing duckweed to grow on excess nutrients generated in dairy farms, farmers can not only increase the production of protein feed and generate added revenue but also limit their dependence on external feed and fertilizer imports.

One of the most useful outputs from the two-objective optimization is the final range of points along the pareto-optimal front. Each of these points represents a unique solution and spatial pattern linked to different combinations of objective functions and constraints and therefore is valuable in aiding the decision-making process regarding the economic and environmental tradeoffs in duckweed farm implementation. Nutrient recovery techniques using aquatic vegetation, such as the one proposed in this study, can potentially be included as part of the Watershed Implementation Plans (WIPs) developed by states in the CBW to implement BMPs for meeting the Chesapeake Bay TMDLs. The total net cost of implementing the required WIP BMPs between 2011 and 2025 was estimated to be approximately \$3.6 billion (in 2010 dollars); and after 2025, it is predicted that the net cost linked to full implementation of all WIP BMPs will be around \$900 million annually (Z. Kaufman et al., 2014). For the scenarios analyzed in this study, implementing duckweed farming would incur a net cost ranging from \$18.1 million (Scenario 4: 4,705 ha duckweed land) to \$252.7 million (Scenario 3: 65,777 ha duckweed land).

While different types of BMPs have been proposed to address water quality issues in the CBW, some are challenging to implement due to their high installation costs. A relative cost analysis conducted by the Chesapeake Bay Foundation illustrated that while small-scale practices such as grassed buffers and conservation tillage would cost \$7.50 per kg of N remediated, stormwater retrofits can get quite expensive at \$1,100/kg (Chesapeake Bay Foundation, 2013). Based on our findings from the different scenarios, the increase in year one net cost for duckweed growing systems would be \$5.30-\$7.70 per kg of N remediated, which is in the lower range of cost/benefit ratios of other established BMPs. With research showing that significant cost savings can be realized through careful selection of cost-effective BMPs and targeted implementation of these BMPs (D. E. Kaufman et al., 2021), implementing circular bioeconomy practices using duckweed in select hotspot counties may be viewed as an environmentally sustainable and economically viable BMP alternative.

4.3.Spatial Analysis

The importance of RE values in impacting water quality in the Bay is clearly documented in past work focusing on the development of CBW TMDLs and has been successfully incorporated in several modeling and optimization studies (D. E. Kaufman et al., 2021; Linker et al., 2013; Robertson & Saad, 2011). Although a majority of hotspot counties selected in our study are known for extensive farming operations (including dairy and alfalfa), some counties with a relatively lower number of dairy farms, such as Luzerne, PA, and Warren, VA, were identified as hotspots for duckweed cultivation primarily due to their high effectiveness of nutrient transport to the Bay (i.e., high RE values). In a related context, many farming-intensive counties in the northern New York region (such as Cortland, Madison, and Otsego, with more than 5,000 dairy cows/county) do not appear in the list of most optimal counties for duckweed production due to their relatively farther distance from the Bay and low effectiveness in nutrient delivery (Figure 2). The same rationale can be linked to why Franklin county, the second most dairy-intensive county in PA, is not as effective as Lancaster in reducing nutrient loads to the Bay.

Even though the decrease in the percentage of land area under alfalfa cultivation is not considerably different in the two optimal cases of scenarios 7 and 8 (40.3% versus 35%), the one with scenario 7 results in more than double the amount of duckweed area due to the full utilization of the removed land for duckweed farming. Employing only part of the alfalfa cropland for duckweed cultivation (replacement strategy ‘b’) as in scenario 8 can provide soil conservation benefits, especially when retiring highly erodible and environmentally sensitive farmlands, as encouraged by the USDA voluntary Conservation Reserve Program (CRP) established through the Food Security Act of 1985 (Bucholtz et al., 2004). In addition, since duckweed grows on a soil-less medium, installing cultivation systems (ex., ponds) on marginal and less fertile lands offers a profitable opportunity to farmers affected by poor crop yields. Leveraging existing marginal lands for various uses is a widely explored research area. Some past work has demonstrated excellent benefits of land-applying manure on marginal lands for increasing productivity (Saha et al., 2021) as well as using these lands to grow perennial crops for bioenergy production (Sanderson & Adler, 2008; Valcu-Lisman et al., 2016). Utilizing similar areas for duckweed cultivation could further enhance the potential use of these less-productive lands to offer additional economic gains for farmers.

One of the challenges we encountered in the spatial pattern analysis was the problem of equifinality. When the optimization variables (RE values and nutrient inputs) are not significantly different between the counties, there is a high likelihood of equifinality, in which different combinations of hotspot locations exhibit similar nutrient reductions (Her & Seong, 2018; Thorp et al., 2015). Therefore, it is necessary to interpret multiple optimal solutions so that only counties that consistently appear as hotspots should be considered for targeted nutrient management. In that context, Lancaster and adjacent counties in central PA are the critical regions for consideration, and the outcomes of this study distinctly prioritize manure management in PA for the overall water quality benefit of the CBW. In addition to several modeling studies validating the nutrient hotspot status of Lancaster (Kleinman et al., 2012; Young et al., 1985), a statewide assessment of PA soils showing the highest presence of excess P in Lancaster soils further supports our finding (Kogelmann et al., 2004). All eight optimization scenarios used in this study highlighted the relevance of considering nutrient delivery factors in designing decision-making tools for spatially targeted nutrient management practices. Expanding this work could involve an integrated watershed modeling approach considering both nutrient runoff potential and effective pollutant transport capability that would help identify critical locations at a finer scale and assess the actual discretized impacts on eutrophication in the Chesapeake Bay.

5. CONCLUSIONS

Spatial optimization of duckweed cultivation locations in the Chesapeake Bay Watershed was conducted in this study to identify hotspot counties that are most critical in terms of manure and fertilizer management. Growing duckweed on dairy manure offers an excellent opportunity to upcycle nutrients that otherwise increase the risk of nutrient transport to surrounding water bodies, leading to water pollution and eutrophication issues in the Chesapeake Bay. Eight different scenarios were designed to evaluate the potential of dairy manure-based duckweed cultivation as an alternative protein production approach to replace alfalfa cropping in the watershed. The optimization runs resulted in similar spatial patterns with the highest land conversions displayed by counties in Pennsylvania (Lancaster and adjacent counties above the Bay) for both duckweed replacement strategies: (a) completely replacing all removed alfalfa land with duckweed cultivation; and (b) partially replacing the removed alfalfa land to maintain only equivalent baseline protein production. Depending on the percentage of alfalfa land available for conversion (10%, 30%, or 50%), the former strategy would help reduce N and P loads by up to 14% and 10%, respectively, and yield up to an additional 68% protein production compared to the existing scenario. While this strategy is associated with a high capital cost, utilizing all of the removed lands for duckweed cultivation has a high return on investment, making it an economical choice in the long run. One area of improvement to expand this study is to include hydrological and stream routing processes in estimating delivery loads since they can highly influence the fate and transport of inland nutrients generated in all the counties. Due to the scale of the study, counties with no dairy production were excluded as variables from optimization. With more data on manure trading between different watershed regions, we could assess how that practice would impact the identification of hotspot locations for targeted manure-based duckweed farming.

Completely transitioning all alfalfa croplands to duckweed farms in counties with dairy operations would ideally result in up to a 23% reduction in N and a 19% reduction in P loads which can play a key role in achieving the Chesapeake Bay TMDL targets. While such a massive agricultural land conversion may seem impractical when considering the economic and cultural barriers, the optimization framework provided here seeks to aid stakeholders in decision-making by offering different types of solutions available for a wide range of environmental and economic constraints. The flexibility in modifying the objective functions and constraints within the framework further extends its applicability to study additional user-defined scenarios and to evaluate their environmental and economic benefits and tradeoffs.

REFERENCES

Adhikari, U., Harrigan, T., & Reinhold, D. M. (2015). Use of duckweed-based constructed wetlands for nutrient recovery and pollutant reduction from dairy wastewater. *Ecological Engineering*, *78*, 6–14. https://doi.org/10.1016/j.ecoleng.2014.05.024

Algren, M., Costello, C., & Landis, A. E. (2022). Phosphorus (P) in animal diets as a driver of embodied P in animal products and net anthropogenic P inputs. *Journal of Industrial Ecology*, *26*(3), 1123–1135. https://doi.org/10.1111/JIEC.13251

Algren, M., Landis, A. E., & Costello, C. (2021). Estimating Virtual Nitrogen Inputs to Integrated U.S. Corn Ethanol and Animal Food Systems. *Environmental Science & Technology*, *55*(12), 8393–8400. https://doi.org/10.1021/ACS.EST.1C02208

Amin, M. G. M., Veith, T. L., Shortle, J. S., Karsten, H. D., & Kleinman, P. J. A. (2020). Addressing the spatial disconnect between national-scale total maximum daily loads and localized land management decisions. *Journal of Environmental Quality*, *49*(3), 613–627. https://doi.org/10.1002/jeq2.20051

Bucholtz, S., Sullivan, P., Hellerstein, D., Hansen, L., Johansson, R., Koenig, S., N. Lubowski, R., D. McBride, W., McGranahan, D., Vogel, S., & Roberts, M. (2004). USDA ERS - The Conservation Reserve Program: Economic Implications for Rural America. In *Agricultural Economic Report No. (AER-834)* (p. 112). https://www.ers.usda.gov/publications/pub-details/?pubid=41678

Calicioglu, O., Femeena, P. V., Mutel, C. L., Sills, D. L., Richard, T. L., Brennan, R. A., Pandara Valappil, F., Mutel, C. L., Sills, D. L., Richard, T. L., & Brennan, R. A. (2021). Techno-economic analysis and life cycle assessment of an integrated wastewater-derived duckweed pond and biorefinery. *ACS Sustainable Chemistry & Engineering*, *9*(28), 9395–9408. https://doi.org/10.1021/ACSSUSCHEMENG.1C02539

Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., & Chen, J. (2011). Spatial multi-objective land use optimization: Extensions to the non-dominated sorting genetic algorithm-II. *International Journal of Geographical Information Science*, *25*(12), 1949–1969. https://doi.org/10.1080/13658816.2011.570269

CBF. (2010). *Chesapeake Bay Foundation*. https://www.cbf.org/

Chesapeake Bay Foundation. (2004). *Manure's Impact on Rivers, Streams and the Chesapeake Bay Keeping Manure Out of the Water Improving manure management to benefit the Chesapeake Bay, Its Rivers, Streams, and the Watershed's Farmers*.

Chesapeake Bay Foundation. (2013). *Pennsylvania Fact Sheet: Cost Effective Pollution Solutions-Getting the Most Benefit from Our Investments*. Chesapeake Bay Foundation.

Chesapeake Bay Program. (2020). *Delivery Factors by Land-River Segment*. Chesapeake Bay Open Data Portal. https://data-chesbay.opendata.arcgis.com/datasets/delivery-factors-by-land-river-segment-1/explore?location=39.785544%2C-77.561000%2C6.98

Cibin, R., & Chaubey, I. (2015). A computationally efficient approach for watershed scale spatial optimization. *Environmental Modelling & Software*, *66*, 1–11. https://doi.org/10.1016/J.ENVSOFT.2014.12.014

Devereux, O. H. (2009). *Estimates of county-level nitrogen and phosphorus data for use in modeling pollutant reduction*. Chesapeake Bay Program and the University of Maryland.

EIP. (2017). *Unsustainable Agriculture: Pennsylvania's manure Hot Spots and their Impact on Local Water Quality and the Chesapeake Bay*. Environmental Integrity Project. https://www.environmentalintegrity.org/wp-content/uploads/2017/08/Unsustainable-Agriculture.pdf

Femeena, P. V., Sudheer, K. P., Cibin, R., & Chaubey, I. (2018). Spatial optimization of cropping pattern for sustainable food and biofuel production with minimal downstream pollution. *Journal of Environmental Management*, *212*, 198–209. https://doi.org/10.1016/J.JENVMAN.2018.01.060

Femeena, P. V., Roman, B., & Brennan, R. A. (2022). The effects of low light intensity on the growth of Lemna minor: Experimental data and an enhanced duckweed growth model. *Environmental and Experimental Botany*, *In review*.

Fernandez Pulido, C. R., Caballero, J., Bruns, M. A., & Brennan, R. A. (2021). Recovery of waste nutrients by duckweed for reuse in sustainable agriculture: Second-year results of a field pilot study with sorghum. *Ecological Engineering*, *168*, 106273. https://doi.org/10.1016/J.ECOLENG.2021.106273

Foster, S., McCuin, G., Nelson, D., Schultz, B., & Torell, R. (2009). *Alfalfa for Beef Cows*. University of Nevada Cooperative Extension. https://extension.unr.edu/publication.aspx?PubID=2228

Her, Y., & Seong, C. (2018). Responses of hydrological model equifinality, uncertainty, and performance to multi-objective parameter calibration. *Journal of Hydroinformatics*, *20*(4), 864–885. https://doi.org/10.2166/hydro.2018.108

Hinkle, M. (2021). Keeping Nutrient Pollution at Bay: An Analysis of Efforts to Mitigate Non-Point Source Pollution in the Chesapeake Bay. *L. Rev*, *291*.

Holly, M. A., Gunn, K. M., Rotz, C. A., & Kleinman, P. J. A. (2019). Management characteristics of Pennsylvania dairy farms**USDA is an equal opportunity provider and employer. *Applied Animal Science*, *35*(3), 325–338. https://doi.org/10.15232/aas.2018-01833

Howarth, R. W., Swaney, D. P., Boyer, E. W., Marino, R., Jaworski, N., & Goodale, C. (2006). The influence of climate on average nitrogen export from large watersheds in the Northeastern United States. In L. A. Martinelli & R. W. Howarth (Eds.), *Nitrogen*

Cycling in the Americas: Natural and Anthropogenic Influences and Controls (pp. 163–186). Springer Netherlands. https://doi.org/10.1007/978-1-4020-5517-1_8

Huque, K. S., Chowdhury, S. A., & Kibria, S. S. (1996). Study on the potentiality of duckweeds as a feed for cattle. *Asian-Australasian Journal of Animal Sciences*, *9*(2), 133–137. https://doi.org/10.5713/ajas.1996.133

Iqbal, S. (2012). *Duckweed Aquaculture Potentials , Possibilities and Limitations for Combined Wastewater Treatment and Animal Feed Production in Developing Countries*.

Jennings, J. (2005). *Alfalfa for Dairy Cattle*. University of Arkansas, United States Department of Agriculture, and County Governments Cooperating.

Jiang, F., Drohan, P. J., Cibin, R., Preisendanz, H. E., White, C. M., & Veith, T. L. (2021). Reallocating crop rotation patterns improves water quality and maintains crop yield. *Agricultural Systems*, *187*, 103015. https://doi.org/10.1016/j.agsy.2020.103015

Jokela, B., & Peters, J. (2009). *Dairy manure nutrients: Variable but valuable* (Issue March). USDA-ARS-Marshfield; Unievrsity of Wisconsin. http://www.soils.wisc.edu/extension/wfapmc/dbsearch.php?yr=2009&auth=jokela&submit=Go

Kang, H., & Sridhar, V. (2018). Assessment of Future Drought Conditions in the Chesapeake Bay Watershed. *JAWRA Journal of the American Water Resources Association*, *54*(1), 160–183. https://doi.org/10.1111/1752-1688.12600

Kaufman, D. E., Shenk, G. W., Bhatt, G., Asplen, K. W., Devereux, O. H., Rigelman, J. R., Ellis, J. H., Hobbs, B. F., Bosch, D. J., Van Houtven, G. L., McGarity, A. E., Linker, L. C., & Ball, W. P. (2021). Supporting cost-effective watershed management strategies for

Chesapeake Bay using a modeling and optimization framework. *Environmental Modelling & Software*, *144*, 105141. https://doi.org/10.1016/j.envsoft.2021.105141

Kaufman, Z., Abler, D., Shortle, J., Harper, J., Hamlett, J., & Feather, P. (2014). Agricultural costs of the Chesapeake Bay total maximum daily load. *Environmental Science and Technology*, *48*(24), 14131–14138. https://doi.org/10.1021/ES502696T/SUPPL_FILE/ES502696T_SI_001.PDF

Kellogg, R. L., Lander, C. H., Moffitt, D. C., & Gollehon, N. (2011). Manure Nutrients Relative to The Capacity Of Cropland And Pastureland To Assimilate Nutrients: Spatial and Temporal Trends for the United States. *Proceedings of the Water Environment Federation*, *2000*(16), 18–157. https://doi.org/10.2175/193864700784994812

Kleinman, P., Blunk, K. S., Bryant, R., Saporito, L., Beegle, D., Czymmek, K., Ketterings, Q., Sims, T., Shortle, J., McGrath, J., Coale, F., Dubin, M., Dostie, D., Maguire, R., Meinen, R., Allen, A., O'Neill, K., Garber, L., Davis, M., … Smith, M. (2012). Managing manure for sustainable livestock production in the Chesapeake Bay Watershed. *Journal of Soil and Water Conservation*, *67*(2), 54A-61A. https://doi.org/10.2489/JSWC.67.2.54A

Kogelmann, W. J., Lin, H. S., Bryant, R. B., Beegle, D. B., Wolf, A. M., & Petersen, G. W. (2004). A statewide assessment of the impacts of phosphorus-index implementation in Pennsylvania. *Journal of Soil and Water Conservation*, *59*(1), 9–18.

Kreider, A. N., Fernandez Pulido, C. R., Bruns, M. A., & Brennan, R. A. (2019). *Duckweed as an Agricultural Amendment: Nitrogen Mineralization, Leaching, and Sorghum Uptake*. *48*(2), 469–475.

Leng, R. (1999). *Duckweed: A tiny aquatic plant with enormous potential for agriculture and environment*. Food and Agricultural Organization, , Animal Production and Health Division. http://www.fao.org/ag/AGAinfo/resources/documents/DW/Dw2.htm

Leng, R., Stambolie, J. H., & Bell, R. (1995). Duckweed—A potential high-protein feed resource for domestic animals and fish. *Livestock Research for Rural Development*, *7*(1).

Linker, L. C., Batiuk, R. A., Shenk, G. W., & Cerco, C. F. (2013). Development of the Chesapeake Bay Watershed Total Maximum Daily Load Allocation. *JAWRA Journal of the American Water Resources Association*, *49*(5), 986–1006. https://doi.org/10.1111/jawr.12105

Liu, Y., Cibin, R., Bralts, V. F., Chaubey, I., Bowling, L. C., & Engel, B. A. (2016). Optimal selection and placement of BMPs and LID practices with a rainfall-runoff model. *Environmental Modelling & Software*, *80*, 281–296. https://doi.org/10.1016/J.ENVSOFT.2016.03.005

Majsztrik, J. C., & Lea-Cox, J. D. (2013). Water Quality Regulations in the Chesapeake Bay: Working to More Precisely Estimate Nutrient Loading Rates and Incentivize Best Management Practices in the Nursery and Greenhouse Industry. *HortScience*, *48*(9), 1097–1102. https://doi.org/10.21273/HORTSCI.48.9.1097

Malczewski, J. (1999). *GIS and Multicriteria Decision Analysis*. John Wiley & Sons.

Maringanti, C., Chaubey, I., & Popp, J. (2009). Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control. *Water Resources Research*, *45*(6). https://doi.org/10.1029/2008WR007094

Najjar, R. G., Pyke, C. R., Adams, M. B., Breitburg, D., Hershner, C., Kemp, M., Howarth, R., Mulholland, M. R., Paolisso, M., Secor, D., Sellner, K., Wardrop, D., & Wood, R. (2010). Potential climate-change impacts on the Chesapeake Bay. *Estuarine, Coastal and Shelf Science*, *86*(1), 1–20. https://doi.org/10.1016/j.ecss.2009.09.026

Oregon State Extension. (2020, January 27). Alfalfa soil fertility and fertilization requirements. *Alfalfa Soil Fertility and Fertilization Requirements*. https://extension.oregonstate.edu/crop-production/pastures-forages/alfalfa-soil-fertility-fertilization-requirements

Pena, L., Oliveira, M., Fragoso, R., & Duarte, E. (2017). *Potential of Duckweed for Swine Wastewater Nutrient removal and Biomass Valorisation through Anaerobic Co-digestion*. 127–138.

Penn State Extension. (2017). *Manure Management Plan Nutrient Balance Worksheet User Guide Completing Nutrient Balance Worksheets for Manure Management Plans*.

Penn State Extension. (2019). *Penn State Crop Cost of Production*.

Ritchie, H., & Roser, M. (2017). *Meat and Dairy Production—Our World in Data*. https://ourworldindata.org/meat-production#global-meat-production

Robertson, D. M., & Saad, D. A. (2011). Nutrient Inputs to the Laurentian Great Lakes by Source and Watershed Estimated Using SPARROW Watershed Models1. *JAWRA Journal of the American Water Resources Association*, *47*(5), 1011–1033. https://doi.org/10.1111/j.1752-1688.2011.00574.x

Robinson, P. H. (2023). *Predicting Feed Intake in Lactating Dairy Cows: Using Theory in Practice*. Cooperative Extension, University of California, Davis.

https://animalscience.ucdavis.edu/sites/g/files/dgvnsk446/files/inline-files/web200006.PDF

Roman, B., Brennan, R. A., & Lambert, J. D. (2021). Duckweed protein supports the growth and organ development of mice: A feeding study comparison to conventional casein protein. *Journal of Food Science*, *86*(3), 1750-3841.15635. https://doi.org/10.1111/1750-3841.15635

Russell, M. J., Weller, D. E., Jordan, T. E., Sigwart, K. J., & Sullivan, K. J. (2008). Net anthropogenic phosphorus inputs: Spatial and temporal variability in the Chesapeake Bay region. *Biogeochemistry 2008 88:3*, *88*(3), 285–304. https://doi.org/10.1007/S10533-008-9212-9

Saha, G. K., Cibin, R., Elliott, H. A., & Preisendanz, H. E. (2021). *Development of a Land Suitability Framework for Sustainable Manure Utilization*. https://scholarsphere.psu.edu/resources/93577832-7a7a-4cdd-b1c7-9a5ca8736c8b

Said, M. Z. M., Culley, D. D., Standifer, L. C., Epps, E. A., Myers, R. W., & Boney, S. A. (1979). Effect of harvest rate, waste loading, and stocking density on the yield of duckweeds. *Proceedings of the World Mariculture Society*, *10*(1–4), 769–780. https://doi.org/10.1111/j.1749-7345.1979.tb00076.x

Sanderson, M. A., & Adler, P. R. (2008). Perennial Forages as Second Generation Bioenergy Crops. *International Journal of Molecular Sciences*, *9*(5), Article 5. https://doi.org/10.3390/ijms9050768

Santos, J. R., Lora, A. T., Exposito, A. G., & Ramos, J. L. M. (2003). Finding improved local minima of power system optimization problems by interior-point methods. *IEEE*

Transactions on Power Systems, *18*(1), 238–244. https://doi.org/10.1109/TPWRS.2002.807097

Shenk, G. W., & Linker, L. C. (2013). Development and Application of the 2010 Chesapeake Bay Watershed Total Maximum Daily Load Model. *JAWRA Journal of the American Water Resources Association*, *49*(5), 1042–1056. https://doi.org/10.1111/JAWR.12109

Soberon, M. A., Cela, S., Ketterings, Q. M., Rasmussen, C. N., & Czymmek, K. J. (2015). Changes in nutrient mass balances over time and related drivers for 54 New York State dairy farms. *Journal of Dairy Science*, *98*(8), 5313–5329. https://doi.org/10.3168/jds.2014-9236

Sońta, M., Rekiel, A., & Batorska, M. (2019). Use of Duckweed L.) in Sustainable Livestock Production and Aquaculture – A Review. *Annals of Animal Science*, *19*(2), 257–271. https://doi.org/10.2478/aoas-2018-0048

Talberth, J., Selman, M., Walker, S., & Gray, E. (2015). Pay for Performance: Optimizing public investments in agricultural best management practices in the Chesapeake Bay Watershed. *Ecological Economics*, *118*, 252–261. https://doi.org/10.1016/j.ecolecon.2015.07.033

Tanuwiria, U. H., & Mushawwir, A. (2020). Hematological and antioxidants responses of dairy cow fed with a combination of feed and duckweed (Lemna minor) as a mixture for improving milk biosynthesis: The effects of feed duckweed. *Biodiversitas Journal of Biological Diversity*, *21*(10), Article 10. https://doi.org/10.13057/biodiv/d211038

Thorp, K. R., Hunsaker, D. J., French, A. N., Bautista, E., & Bronson, K. F. (2015). Integrating geospatial data and cropping system simulation within a geographic information system to analyze spatial seed cotton yield, water use, and irrigation requirements. *Precision Agriculture*, *16*(5), 532–557. https://doi.org/10.1007/s11119-015-9393-x

Timmerman, M., & Hoving, I. E. (2016). *Purifying manure effluents with duckweed*. Wageningen UR Livestock Research.

Toscano, G., Hernandez–Suarez, J. S., Blank, J., Nejadhashemi, P., Deb, K., & Linker, L. (2022). Large-scale Multi-objective Optimization for Water Quality in Chesapeake Bay Watershed. *2022 IEEE Congress on Evolutionary Computation (CEC)*, 01–09. https://doi.org/10.1109/CEC55065.2022.9870286

USEPA. (2010). *Chesapeake Bay TMDL Fact Sheet*.

Valcu-Lisman, A. M., Kling, C. L., & Gassman, P. W. (2016). The Optimality of Using Marginal Land for Bioenergy Crops: Tradeoffs between Food, Fuel, and Environmental Services. *Agricultural and Resource Economics Review*, *45*(2), 217–245. https://doi.org/10.1017/age.2016.20

Vrugt, J. A., & Robinson, B. A. (2007). Improved evolutionary optimization from genetically adaptive multimethod search. *Proceedings of the National Academy of Sciences*, *104*(3), 708–711. https://doi.org/10.1073/PNAS.0610471104

Wang, G., Han, Q., & de vries, B. (2021). The multi-objective spatial optimization of urban land use based on low-carbon city planning. *Ecological Indicators*, *125*, 107540. https://doi.org/10.1016/j.ecolind.2021.107540

Young, C. E., Crowder, B. M., Shortle, J. S., & Alwang, J. R. (1985). Nutrient management on dairy farms in southeastern Pennsylvania. *Journal of Soil and Water Conservation*, *40*(5), 443–445.

Zhang, X., Srinivasan, R., & Van Liew, M. (2008). Multi-Site Calibration of the SWAT Model for Hydrologic Modeling. *Transactions of the ASABE*, *51*(6), 2039–2049. https://doi.org/10.13031/2013.25407

Zhao, Y., Fang, Y., Jin, Y., Huang, J., Bao, S., Fu, T., He, Z., Wang, F., Wang, M., & Zhao, H. (2015). Pilot-scale comparison of four duckweed strains from different genera for potential application in nutrient recovery from wastewater and valuable biomass production. *Plant Biology*, *17*(s1), 82–90. https://doi.org/10.1111/plb.12204