



Modeling Workgroup Meeting Quarterly Review

April 2024

Optimization Update

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MICHIGAN STATE UNIVERSITY

AGENDA

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Timeline

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Overview of the presentation

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Presenting the improved optimization platform & Results

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2024 Chesapeake Bay Optimization Webinars

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Initial optimization runs for Lancaster County, PA

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Products (Papers and Presentations)

7

Next Steps

Timeline of the Project

Calendar Year	2020				2021				2022				2023				2024				2025				2026
Calendar Quarter	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	
Project Year	Year 1				Year 2				Year 3				Year 4				Year 5				Year 6				
Task 1: Development of an efficient single-objective optimization procedure for cost-effective BMP allocation																									
1.1: Understanding CAST modules and effect of BMPs on objectives and constraints																									
1.2: Development of a simplified point-based structured single-objective optimization procedure																									
1.3: Development of a hybrid customized single-objective optimization procedure																									
1.4: Verification and validation with CBP users and decision-makers and update of optimization procedure																									
Task 2: Development of an efficient multi-objective (MO) optimization procedure for cost-loading trade-off BMP allocation																									
2.1: Develop generative MO optimization using hybrid optimization procedure developed at Task 1																									
2.2: Develop simultaneous MO customized optimization using population-based evolutionary algorithms																									
2.3: Comparison of generative & simultaneous procedures and validation with CBP users & decision-makers																									
2.4: Develop an interactive multi-criterion decision-making aid for choosing a single preferred solution																									
Task 3: Multi-state implementation using machine learning and parallel computing platforms																									
3.1: Comparative study to choose a few best performing methods																									
3.2: Scalability to State and Watershed level Scenarios																									
3.3: “Innovization” approach for improving scalability																									
3.4: Distributed computing approach for improving scalability																									
Task 4: Interactive optimization and decision-making using user-friendly dashboard																									
4.1: User-friendly optimization through a dashboard																									
4.2: Surrogate-assisted optimization procedures																									
4.3: Robust optimization method for handling uncertainties in variables and parameters																									
4.4: Sustainable watershed management practices																									

We are here

Task 3: Multi-state implementation using machine learning and parallel computing platforms

3.1 Comparative study to choose a few best performing methods

3.2 Scalability to state and watershed level scenarios

3.3 “Innovization” approach for improving scalability

3.4 Distributed computing approach for improving scalability

Timeline of the Project



Presenting the improved optimization platform

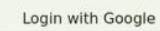
BY GREGORIO TOSCANO

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An Application to the Entire Chesapeake Bay Watershed

Total variables: **2,224,135**

Total constraints: **297,951**

A large-scale optimization problem

%Nitrogen Reduction

Cost

Base Scenario (lbs)

Nitrogen	381,952,658
Phosphorus	26,537,669
Sediments	43,088,072,344

Legend

Cost (\$)

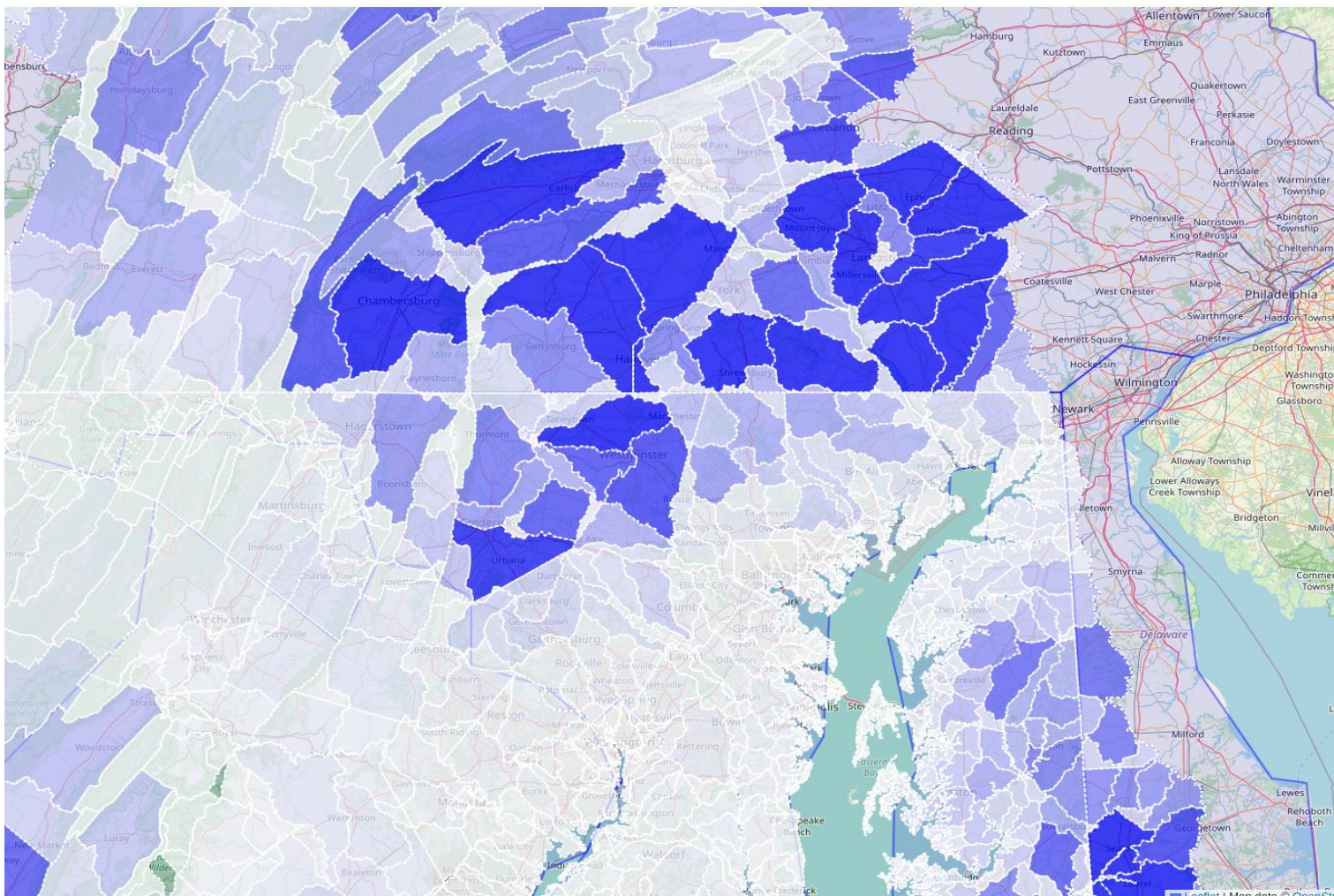
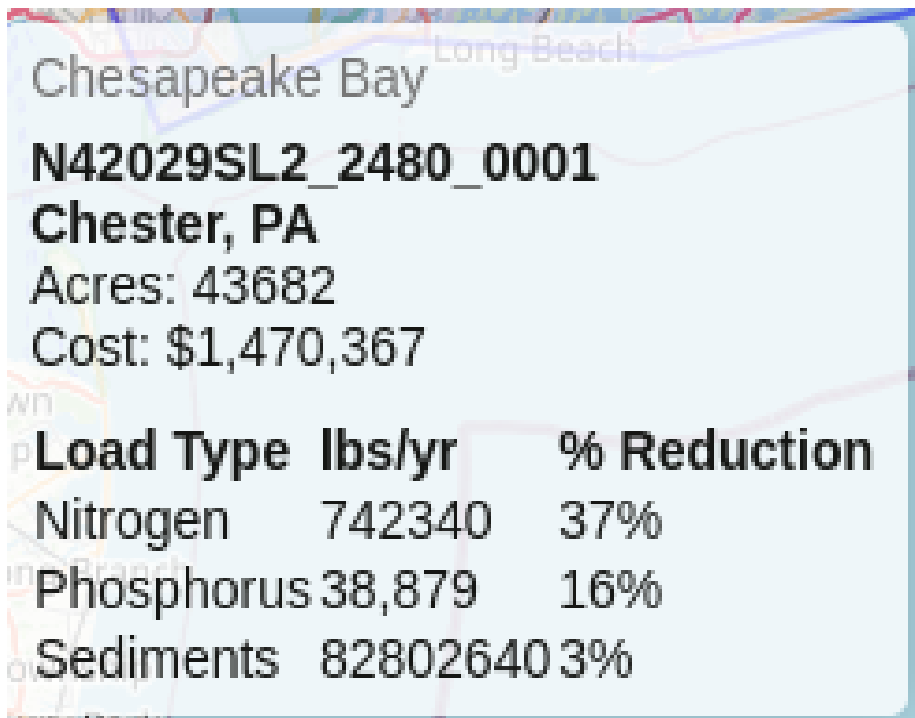
- \$0 - \$500,000
- \$500,000 - \$1,000,000
- \$1,000,000 - \$1,500,000
- \$1,500,000 - \$2,000,000

Nitrogen Reduction (%)

- 0% - 12.5%
- 12.5% - 25%
- 25% - 37.5%
- 37.5% - 50%

After 12 hours of execution

Looking at a Specific County from the Watershed



Chesapeake Bay Optimization Webinars

Join experts in the discussion
of bay preservation.



COMING UP
IN 2024



Goal of the Webinar

Our **goal** is to test and evaluate the optimization strategies of the Chesapeake Bay watershed optimization project against real-world conditions.

- Discuss all capabilities and flexibilities of the optimization software
- Demonstrate how to set-up a county, counties, state or states for finding optimal BMP allocations for cost/loading
- Demonstrate how to use the optimization routines
- Discuss how to evaluate the optimization results

Initial Discussions Towards the Webinar

We had an initial meeting with Olivia Devereux, Lew Linker, Jessica Rigelman, Helen Golimowski to discuss the location and point of contact for development of webinar series.

- We shall discuss further and finalize a suitable day of the seminar in 2024
- Besides demonstration of the optimization software, participants will have a hands-on experience in **setting up** an optimization run and **analyze optimization results**

A light green brushstroke background with a textured, painterly appearance, featuring various shades of green and some darker green accents.

Analyzing Optimization Results

Study Area

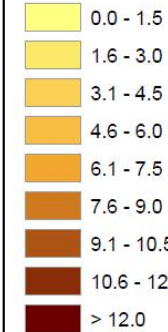
- Pennsylvania's Phase 3 Watershed Implementation Plan
- Lancaster county

All Sources of Total Nitrogen

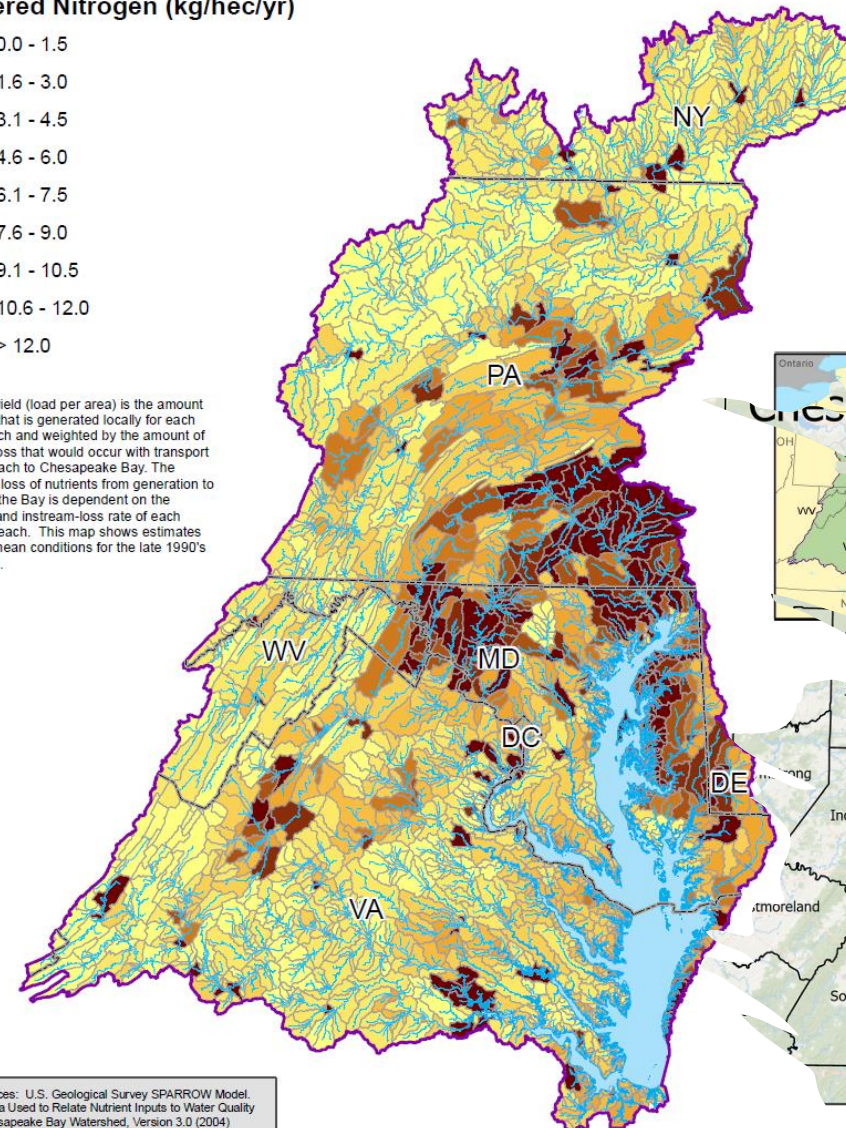
Delivered Yield to the Chesapeake Bay



Delivered Nitrogen (kg/hect/yr)

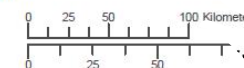


Delivered yield (load per area) is the amount of nutrient that is generated locally for each stream reach and weighted by the amount of in-stream loss that would occur with transport from the reach to Chesapeake Bay. The cumulative loss of nutrients from generation to delivery to the Bay is dependent on the traveltime and in-stream-loss rate of each individual reach. This map shows estimates based on mean conditions for the late 1990's time period.

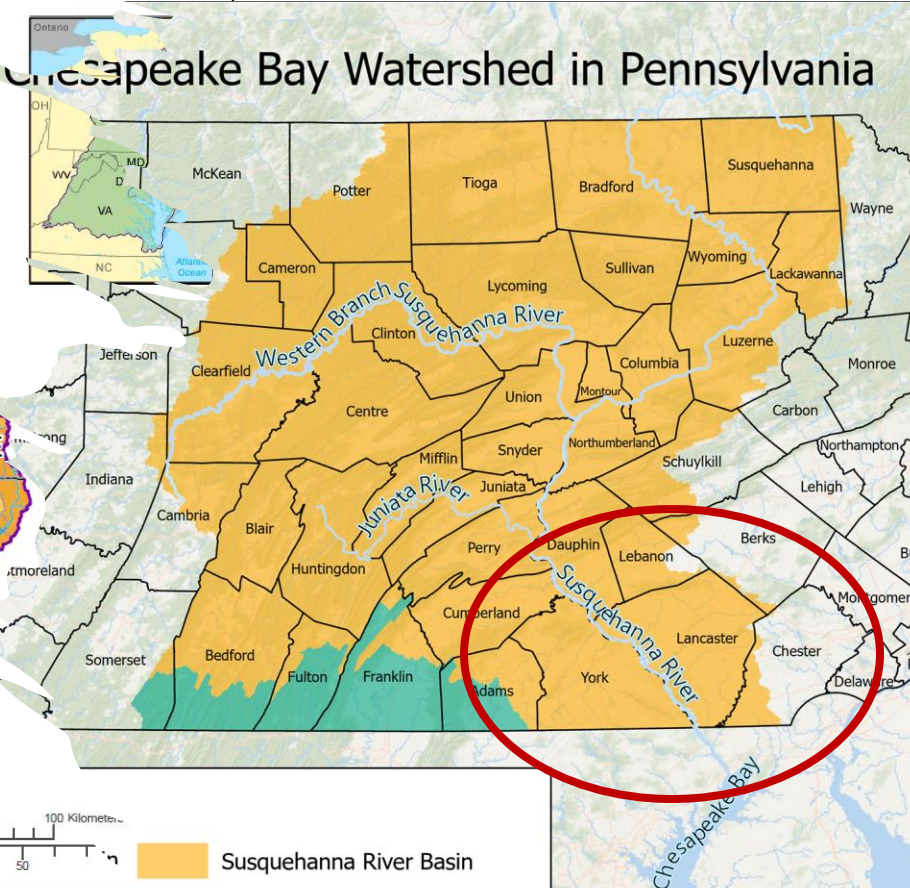


Data Sources: U.S. Geological Survey SPARROW Model, Digital Data Used to Relate Nutrient Inputs to Water Quality in the Chesapeake Bay Watershed, Version 3.0 (2004) (<http://md.water.usgs.gov/publications/ofr-2004-1433/>)

For more information, visit www.chesapeakebay.net
Disclaimer: www.chesapeakebay.net/termsfuse.htm



Chesapeake Bay Watershed in Pennsylvania



Susquehanna River Basin

Scenarios for NSGA-III Optimization

Study Area: Lancaster County, PA

	2019 Base Scenario (lbs)
Nitrogen	30,448,456
Phosphorus	1,537,509
Sediments	1,166,578,352

Two Scenarios:

Scenario 1:

- Lancaster county
- All BMPs (306)
- **Constraint: 25-50% N reductions, no cost constraint**
- **22,346 variables, 3,103 constraints**

Scenario 2:

- Lancaster county
- Preferred BMPs (206)
- **Constraint: 25-50% N reductions, no cost constraint**
- **20,122 variables, 2,180 constraints**



Priority BMPs include:

- Livestock exclusion fencing
- Stream-side buffers
- Streambank restoration
- Barnyard and feedlot runoff abatement
- Stream crossings
- Off-stream watering
- Manure storage facilities
- Nutrient management plans and manure management plans
- Conservation plans or agricultural erosion and sedimentation plans
- Cover crops
- Any other priority practices approved by the Commission

LANCASTER COUNTY COMMUNITY CLEAN WATER IMPLEMENTATION TOOLBOX

**Implementing a County-Based Action Plan
for Clean Water**

January 2020

Alternate Trade-off Solutions

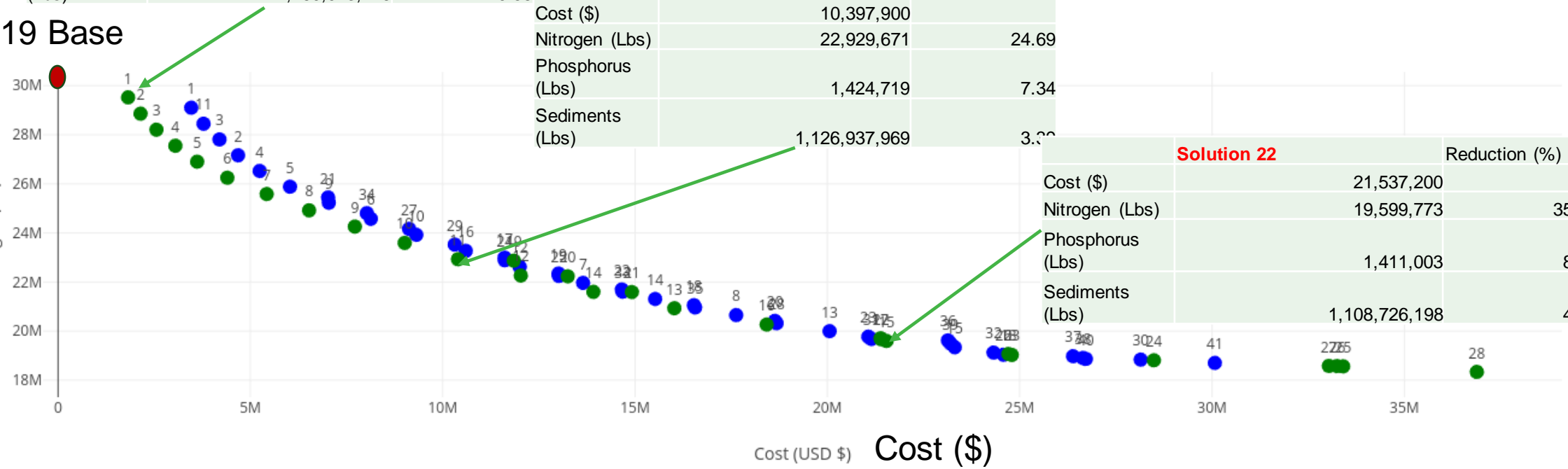
	Base Scenario (lbs)
Nitrogen	30,448,456.91
Phosphorus	1,537,509.50
Sediments	1,166,578,352.85

	Solution 1	Reduction (%)
Cost (\$)	1,822,750	
Nitrogen (Lbs)	29,523,075	3.04
Phosphorus (Lbs)	1,511,147	1.71
Sediments (Lbs)	1,160,023,276	0.56

	Solution 11	Reduction (%)
Cost (\$)	10,397,900	
Nitrogen (Lbs)	22,929,671	24.69
Phosphorus (Lbs)	1,424,719	7.34
Sediments (Lbs)	1,126,937,969	3.00

	Solution 22	Reduction (%)
Cost (\$)	21,537,200	
Nitrogen (Lbs)	19,599,773	35.63
Phosphorus (Lbs)	1,411,003	8.23
Sediments (Lbs)	1,108,726,198	4.95

2019 Base
Remaining N₂ (lbs)

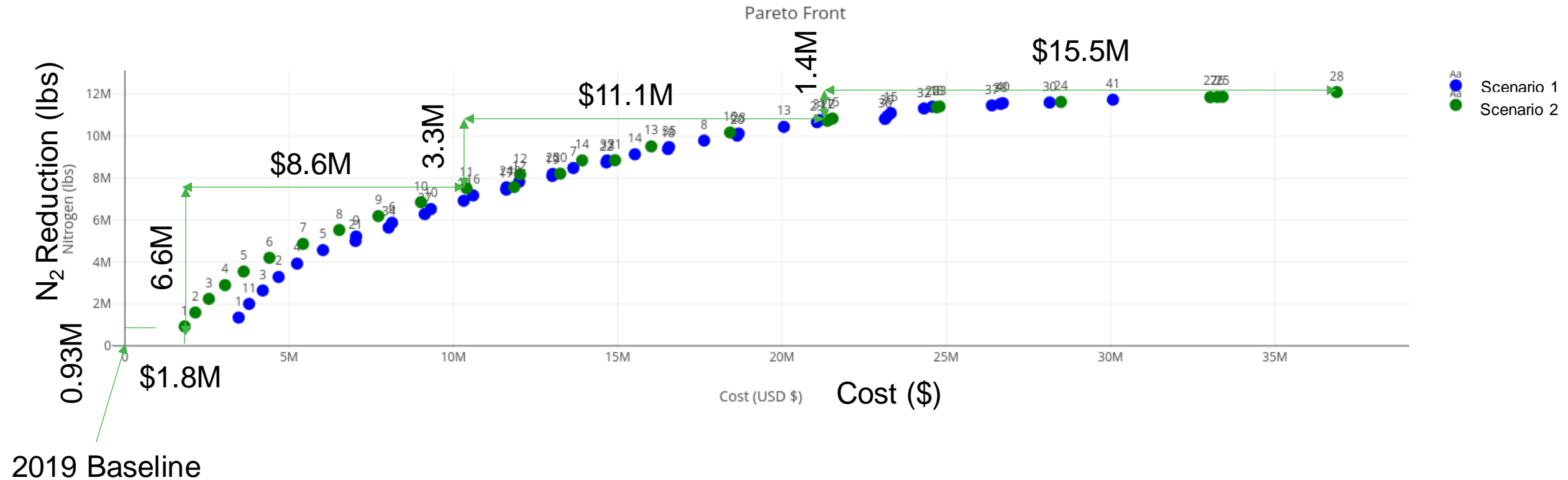


Scenario 1
Scenario 2

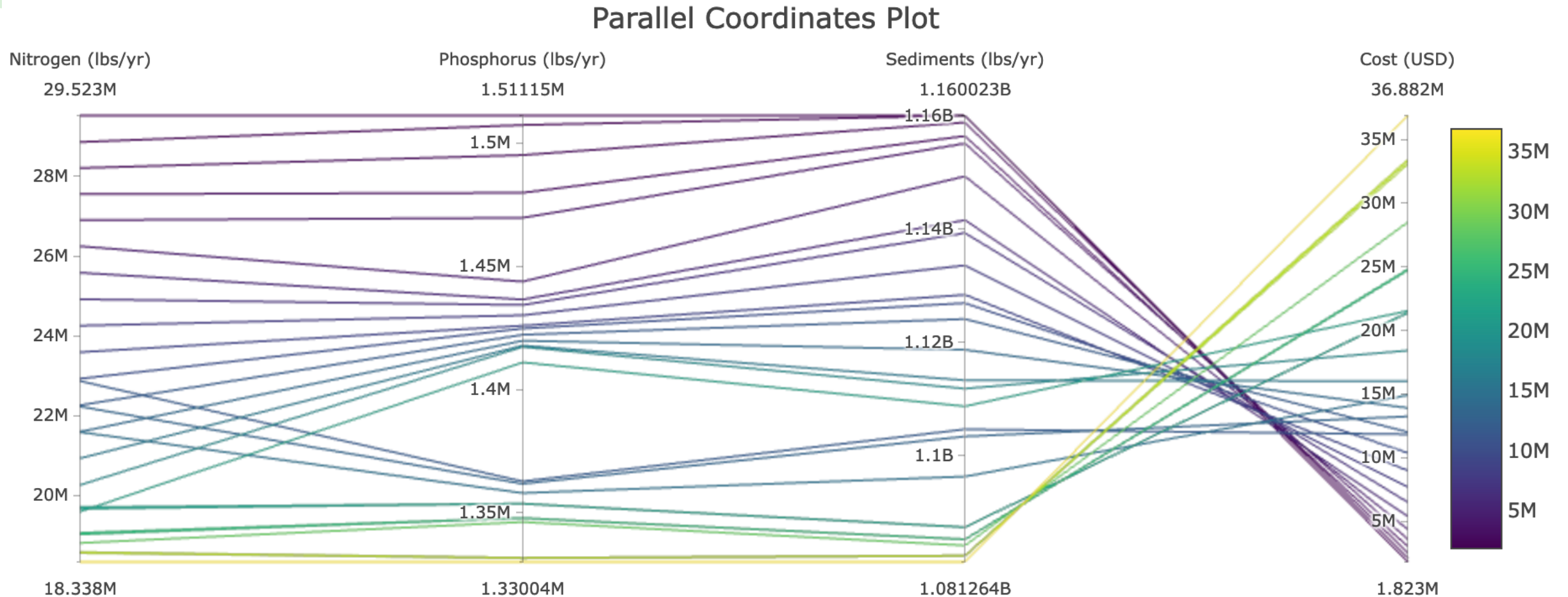
	Base Scenario	Solution 1	Reduction (%)	Solution 11	Reduction (%)	Solution 22	Reduction (%)
Cost (\$)		1,822,750		10,397,900		21,537,200	
Nitrogen (Lbs)	30,448,457	925,382	3.04	7,518,786	24.69	10,848,684	35.63
Phosphorus (Lbs)	1,537,509	26,362	1.71	112,790	7.34	126,506	8.23
Sediments (Lbs)	1,166,578,353	6,555,077	0.56	39,640,384	3.40	57,852,155	4.96

Alternate Trade-off Solutions Using Multi-objective Optimization

Trade-off Analysis

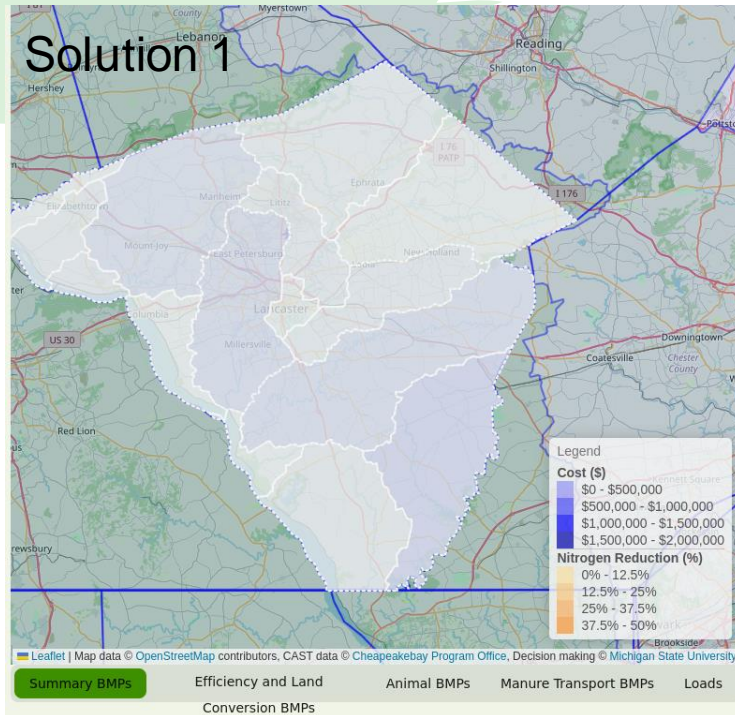


Alternate Trade-off Solutions for Scenario 2 (Well Optimized)

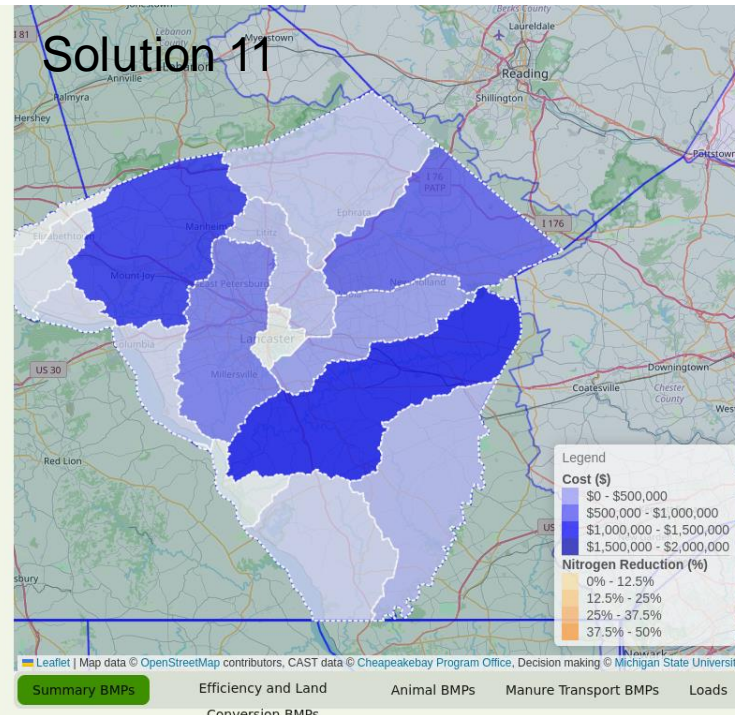


Loads are correlated, but have a trade-off with cost

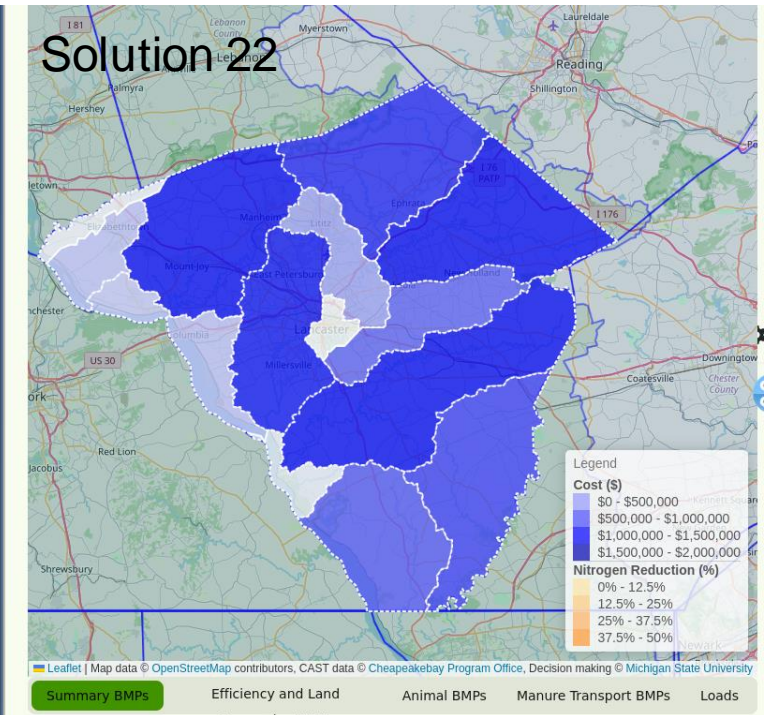
Comparison of Three Alternate BMP Allocation Schemes having Different Costs



Id	County	Bmp	Amount	Actions
1	Lancaster, PA	Off Stream Watering Without Fencing	1395.44	
2	Lancaster, PA	Nutrient Management Plan High Risk Lawn	141.80	
3	Lancaster, PA	Land Retirement to Ag Open Space	22.46	
4	Lancaster, PA	Grass Buffer	239.19	
5	Lancaster, PA	Forest Buffer	93.22	
6	Lancaster, PA	Nutrient Management N Rate	2392.91	



Id	County	Bmp	Amount	Actions
1	Lancaster, PA	Nutrient Management N Rate	2392.91	
2	Lancaster, PA	Off Stream Watering Without Fencing	1395.44	
3	Lancaster, PA	Barnyard Runoff Control	61.60	
4	Lancaster, PA	Nutrient Management Plan High Risk Lawn	141.80	
5	Lancaster, PA	Land Retirement to Ag Open Space	22.46	
6	Lancaster, PA	Grass Buffer	239.19	
7	Lancaster, PA	Nutrient Management N Timing	2150.33	
8	Lancaster, PA	Nutrient Management N Placement	2645.13	
9	Lancaster, PA	Cover Crop Traditional Rye Early Drilled	422.28	
10	Lancaster, PA	Forest Buffer	93.22	



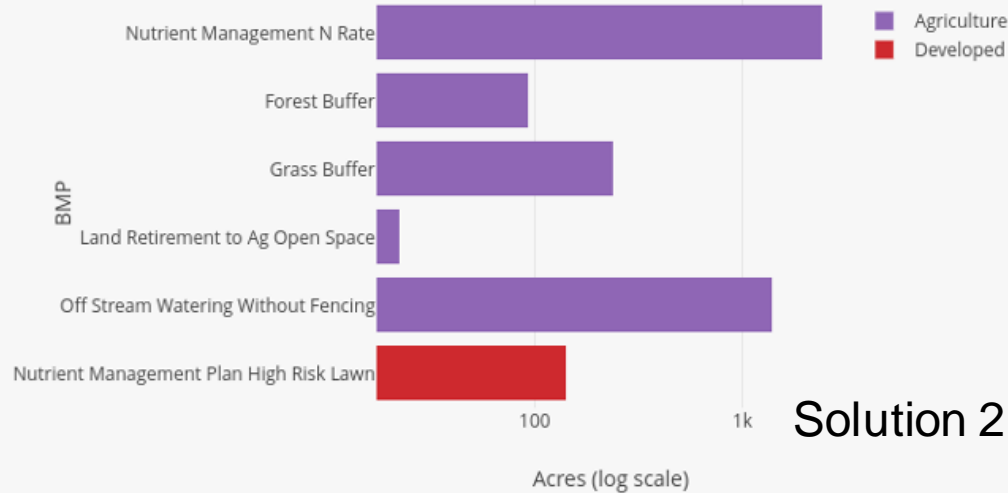
Id	County	Bmp	Amount	Actions
1	Lancaster, PA	Nutrient Management N Rate	422.28	
2	Lancaster, PA	Cover Crop Traditional Rye Early Drilled	2150.33	
3	Lancaster, PA	Off Stream Watering Without Fencing	1395.44	
4	Lancaster, PA	Barnyard Runoff Control	61.60	
5	Lancaster, PA	Nutrient Management Plan High Risk Lawn	141.80	
6	Lancaster, PA	Land Retirement to Ag Open Space	126.62	
7	Lancaster, PA	Grass Buffer	462.36	
8	Lancaster, PA	Nutrient Management N Placement	2392.91	
9	Lancaster, PA	Nutrient Management N Timing	2150.33	
10	Lancaster, PA	Forest Buffer	330.49	

- More BMPs are used for more reduction of N₂
- LRSs use different BMPs and costs

Summary of Comparison of Three Alternate Solutions

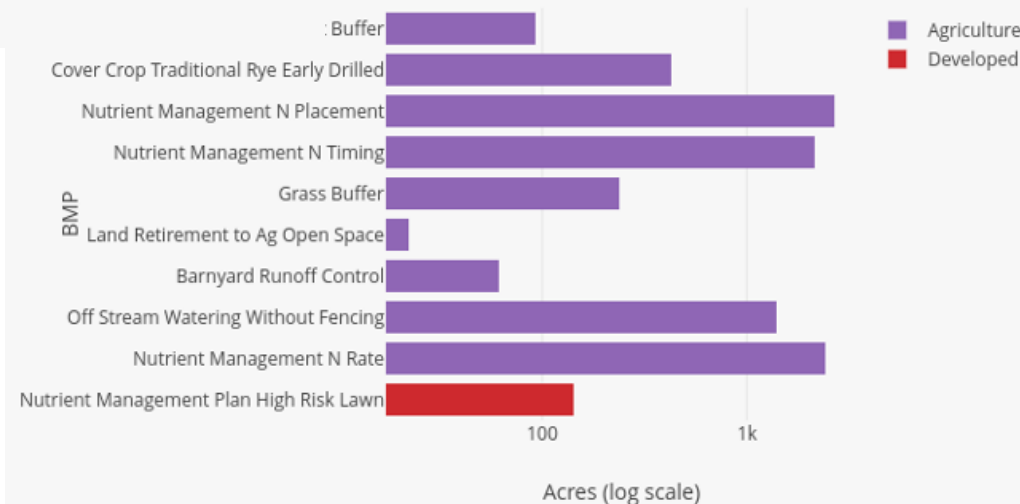
Solution 1

Implemented BMPs



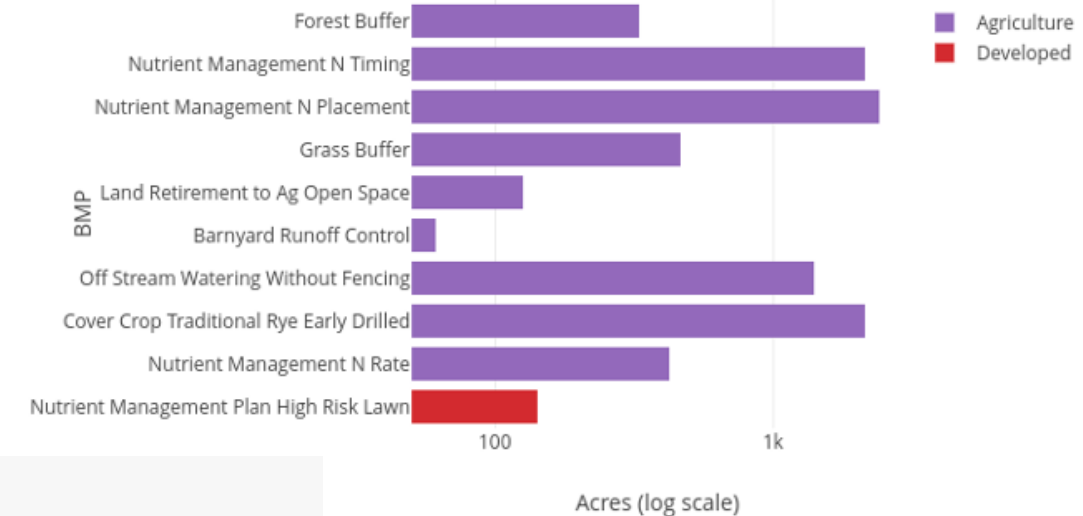
Solution 2

Implemented BMPs



Solution 3

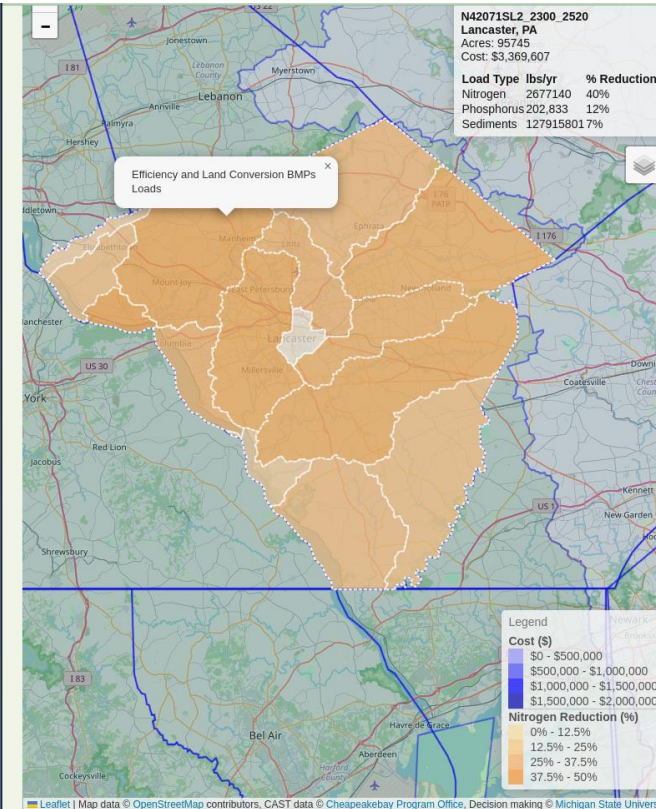
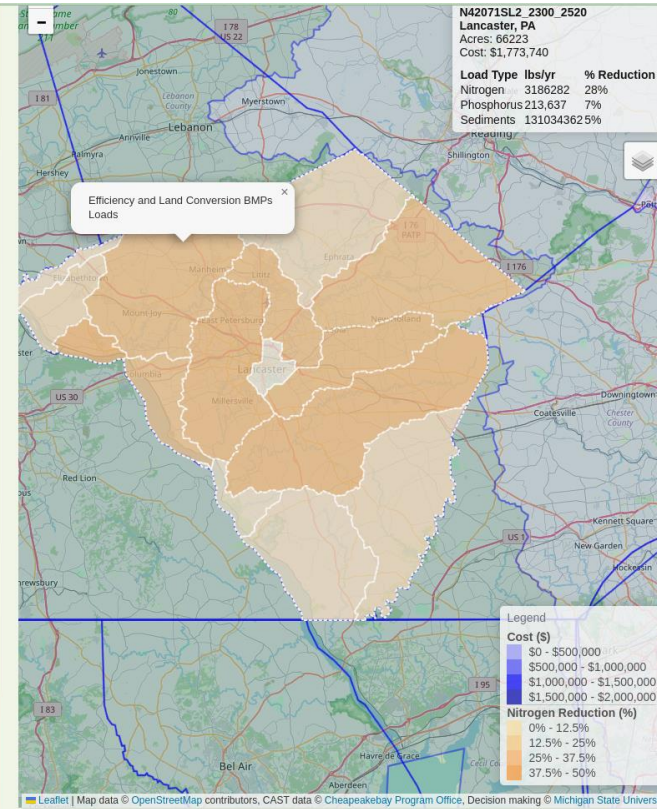
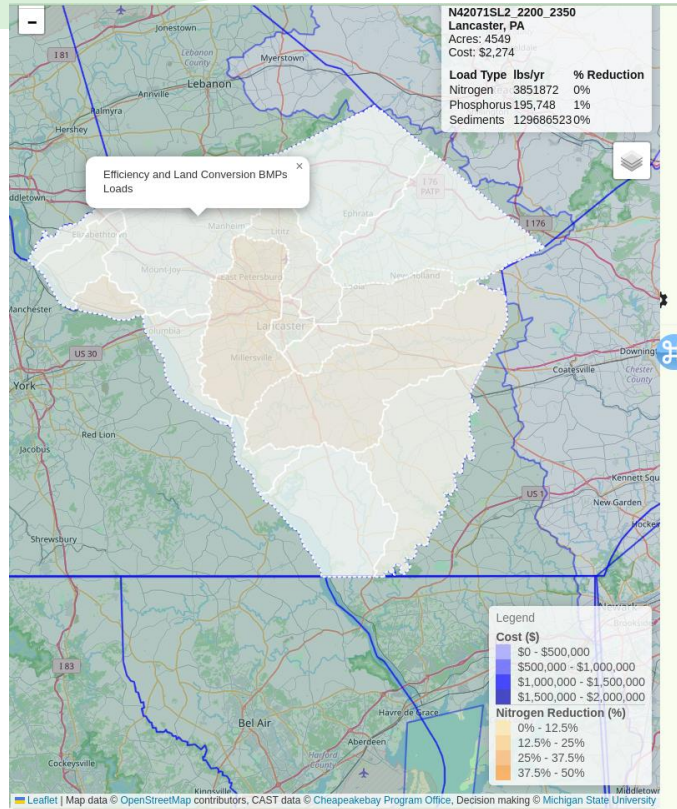
Implemented BMPs



The BMP allocation schemes can provide an idea of

- How more N₂ is reduced
- Why cost is increased

Comparison of Three Alternate Solutions in Terms of Loads on LRS-1



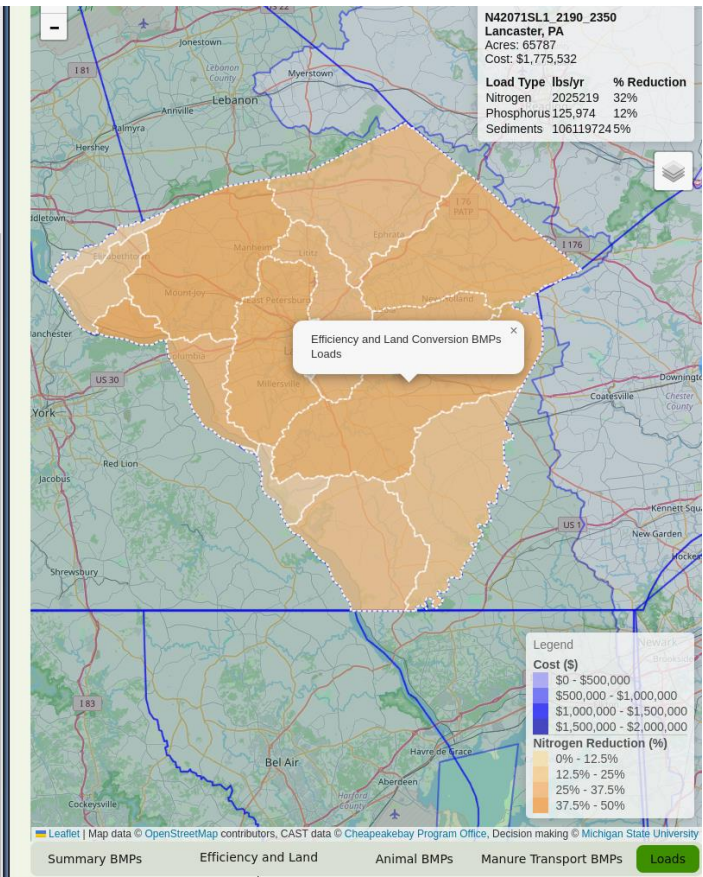
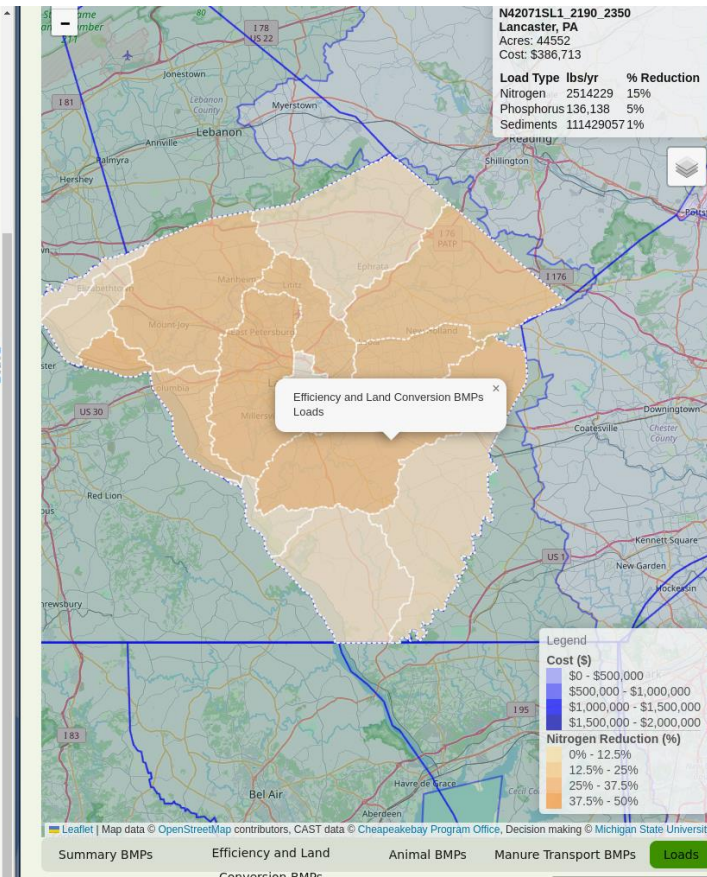
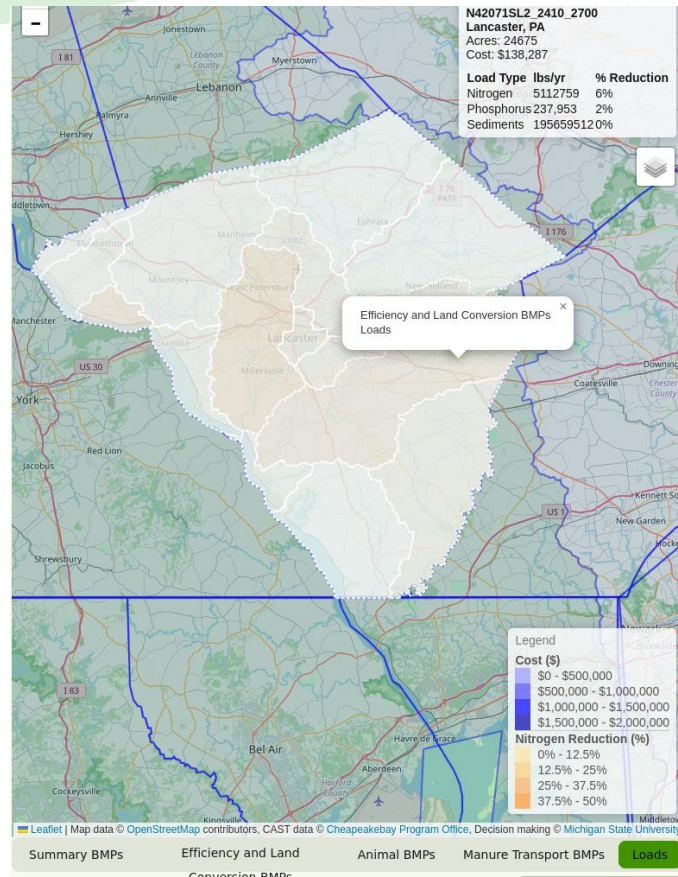
Discover patterns and create knowledge base

Remaining					
State	County	Lrs	Sector	Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2300_2520	Agriculture	3,845,629	191,071
PA	Lancaster	N42071SL2_2300_2520	Developed	394,759	15,163
PA	Lancaster	N42071SL2_2300_2520	Natural	94,265	19,245
PA	Lancaster	N42071SL2_2300_2520	Septic	42,089	0

Remaining					
State	County	Lrs	Sector	Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2300_2520	Agriculture	2,712,279	181,155
PA	Lancaster	N42071SL2_2300_2520	Developed	351,317	14,159
PA	Lancaster	N42071SL2_2300_2520	Natural	80,595	18,321
PA	Lancaster	N42071SL2_2300_2520	Septic	42,089	0

Remaining					
State	County	Lrs	Sector	Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2300_2520	Agriculture	2,208,984	171,194
PA	Lancaster	N42071SL2_2300_2520	Developed	351,317	14,159
PA	Lancaster	N42071SL2_2300_2520	Natural	74,749	17,479
PA	Lancaster	N42071SL2_2300_2520	Septic	42,089	0

Comparison of Three Alternate Solutions in Terms of Loads on LRS-2



Similar patterns exist in LRS-2

State	County	Lrs	Sector	Remaining Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2410_2700	Agriculture	4,426,838	199,942
PA	Lancaster	N42071SL2_2410_2700	Developed	474,395	13,586
PA	Lancaster	N42071SL2_2410_2700	Natural	146,579	24,424
PA	Lancaster	N42071SL2_2410_2700	Septic	64,945	0

State	County	Lrs	Sector	Remaining Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2410_2700	Agriculture	3,170,195	186,672
PA	Lancaster	N42071SL2_2410_2700	Developed	434,382	12,923
PA	Lancaster	N42071SL2_2410_2700	Natural	136,167	22,952
PA	Lancaster	N42071SL2_2410_2700	Septic	64,945	0

State	County	Lrs	Sector	Remaining Nitrogen (lbs/yr)	Phosphorus (lbs/yr)
PA	Lancaster	N42071SL2_2410_2700	Agriculture	2,735,282	176,840
PA	Lancaster	N42071SL2_2410_2700	Developed	434,382	12,923
PA	Lancaster	N42071SL2_2410_2700	Natural	124,689	21,913
PA	Lancaster	N42071SL2_2410_2700	Septic	64,945	0

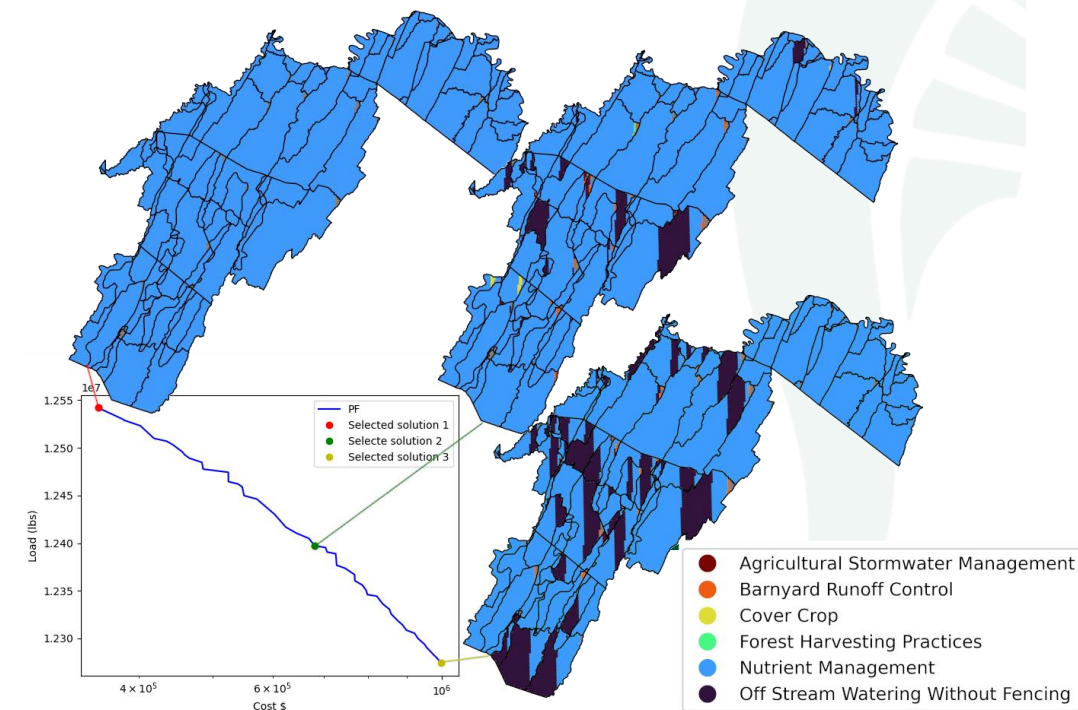


Products (Papers and Presentations)

Large-Scale Multiobjective Optimization for Watershed Planning and Assessment

Gregorio Toscano-Pulido^{1b}, Hoda Razavi^{1b}, Graduate Student Member, IEEE, A. Pouyan Nejadhashemi^{1b}, Kalyanmoy Deb^{1b}, Fellow, IEEE, and Lewis Linker

Our Journal published Paper 2024



Abstract—Selecting the appropriate best management practices (BMPs) is crucial for reducing pollution levels and improving the watershed’s water quality. However, identifying cost-effective BMP combinations for various locations is challenging, especially when using computationally expensive evaluation procedures like the Chesapeake Assessment Scenario Tool (CAST). This study presents a customized and hybrid evolutionary multiobjective optimization (EMO) algorithm aimed at enhancing the water quality in the Chesapeake Bay Watershed for two conflicting objectives: 1) cost of BMP implementation and 2) the amount of resulting nitrogen loading to streams. First, we present a surrogate model-based optimization approach and evaluate its accuracy and execution time against the CAST evaluation system. Then, we present a hybrid two-stage EMO procedure, which is initialized with solutions obtained from a point-based ϵ -constraint procedure and works with a repair operator to satisfy equality constraints. The hybrid EMO procedure yields a set of nondominated tradeoff solutions for problems with as few as 1012 variables (West Virginia’s Tucker County) to as large as 153818 variables (the whole state of West Virginia). Alternate tradeoff solutions provide a knowledge of different possible options and also importantly provide a flexible method of arriving at a single preferred solution for deployment. The EMO procedure is then integrated with CAST using recent RESTful API approaches, and interesting accuracy versus computational tradeoffs are discussed. Finally, a number of interesting insights of the scale-up optimization study reveal promising strategies to scale the application to multiple counties and the watershed level.

Index Terms—Best management practices (BMPs), Chesapeake Bay Watershed (CBW), evolutionary multiobjective optimization (EMO), hybrid approach, large-scale optimization, watershed optimization.

I. INTRODUCTION

MANY anthropogenic activities are directly or indirectly affecting water quality and aquatic habitats. For

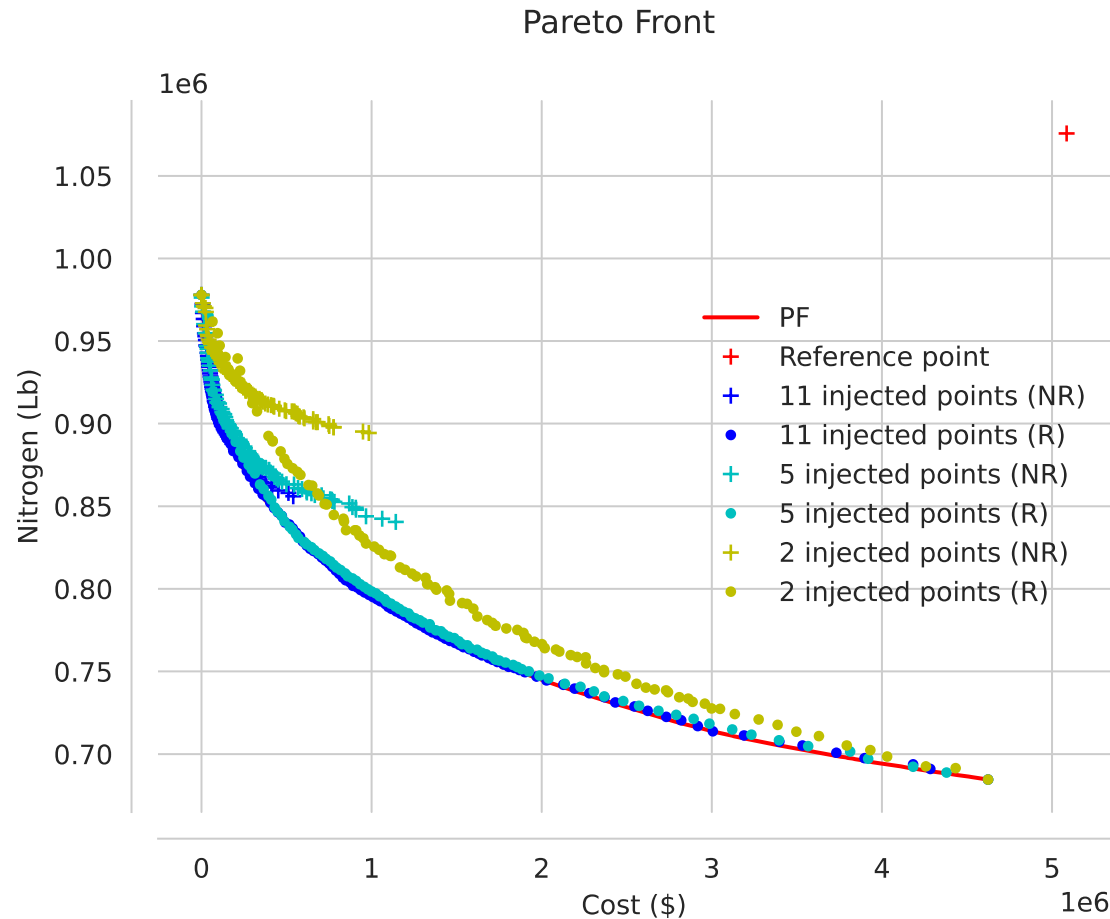
example, agriculture requires the application of fertilizers and manures that produce crops, but when applied in excess, can ultimately discharge into waterbodies, resulting in water quality degradation in the form of eutrophication and hypoxia in the Chesapeake Bay, Gulf of Mexico [2], and other coastal waters [20]. This is a concern as most nutrient pollution in the Chesapeake and Gulf of Mexico is from nonpoint sources, and their control and regulation are challenging [11]. Nutrient export from agricultural lands can be due to many reasons, including the heterogeneity of the agricultural landscape, the lack of regulatory enforcement to control fertilizer or manure application rate and amount, climate variability, and groundwater and surface water interactions [10], [11].

In order to control agrochemical discharge to waterbodies, both structural and nonstructural measures known as best management practices (BMPs) have been introduced and standardized by many agencies, including the Natural Resources Conservation Service (NRCS) [14]. However, their performance level varies by both physiographical (e.g., soil type and slope) and climatological (e.g., rainfall intensity, dry spell) factors. Therefore, BMP performance not only depends on the design characteristics but is also influenced by the location of the implementation site. Meanwhile, the level of complexity can exponentially increase as many types of BMPs can be implemented on the same parcel of land and in thousands of locations throughout a watershed [21]. Furthermore, considering all these factors in developing a watershed restoration plan can be a massive undertaking as numerous factors must be simultaneously considered [21].

To address these issues, watershed and water quality models have been widely adopted by water resource managers. However, despite their effectiveness in handling large and complex watershed planning through model scenarios, each scenario can only consider a single large-scale BMP implementation strategy. Evaluating the most cost-effective strategy

Conference paper

2023 IEEE Congress on Evolutionary Computation (CEC), Chicago



Utilizing Innovization to Solve Large-scale Multi-objective Chesapeake Bay Watershed Problem

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Abstract—Innovization is a task for analyzing multiple Pareto-optimal solutions obtained by an evolutionary multi-objective optimization (EMO) algorithm to extract common features in the decision variables, leading to design rules or solution principles. The principles derived from innovized principles can provide valuable insights to the users about “how to create an optimal solution?”. Manual or automated machine learning-based innovization methods were proposed in the literature to extract innovized principles in a problem. Although different problems may demand different structures of the rules, the innovized rules can also be utilized to improve the performance of the subsequent iterations of the optimization algorithm or help in executing an efficient re-optimization of the same problem. In this paper, we consider a large-scale and multi-objective complex optimization task of minimizing cost and nitrogen loading in certain counties within the Chesapeake Bay Watershed (CBW) and find multiple trade-off solutions using the NSGA-III approach applied to the CBW’s real evaluator tool (The Chesapeake Assessment Scenario Tool-CAST). 205 Best Management Practices (BMPs) are considered to be implemented at each land-river segment within a county, leading to as many as 65,260 variables for the resulting multi-objective optimization procedure. First, hundreds of trade-off solutions found by the CAST-NSGA-III procedure are analyzed manually to find the top-most BMPs used in them. After that, a re-optimization of CAST-NSGA-III is run with a few critical BMPs (resulting in a decrease of the variable to a range between 3% and 33%) found to commonly appear in the trade-off solution set of the previous runs. Interestingly, the resulting trade-off front with reduced BMPs is similar to the original run achieved with tens of thousands of variables. The findings are intriguing and demonstrate the efficacy of innovization in addressing intricate, real-world issues at a significant scale.

Index Terms—Innovization, Watershed Management, Large-scale Optimization, Multi-objective Optimization

I. INTRODUCTION

Most practical search and optimization problems involve more than one conflicting objective. By definition, these problems have not one but multiple trade-off Pareto-optimal solutions. While conventional methods scalarize multiple objectives into a single criterion [1], these methods suffer from several shortcomings. First, the scalarization method requires additional preference information of objectives over the entire

with a different parameter setting without any gain in computational effort from multiple runs.

Recent population-based optimization methods, such as evolutionary multi-objective optimization (EMO) algorithms, have been shown to find and store multiple Pareto-optimal solutions in a single application [2], [3]. This is one sole reason why these methods have become increasingly popular. A by-product of finding multiple Pareto-optimal solutions is that, being optimal, these solutions are likely to possess certain common properties among their variables, objective, and constraint values. Finding Pareto-optimal solutions and analyzing them to reveal common properties was termed as the task of *innovization* [4]. The name is so given due to the fact that the common properties often lead to new and innovative properties involving problem parameters [5]–[7]. When the Pareto-optimal solutions are analyzed to unveil such common hidden properties (or rules), the rules are helpful as knowledge, which can then be used to enhance future optimizations of similar problems.

The Chesapeake Bay is the largest estuary in the United States and the third-largest in the world. As a result, the Bay has enormous historical, social, economic, and ecological importance, with natural benefits estimated at more than \$100 billion per year [8]. With a drainage area of about 166,000 km², the Chesapeake Bay Watershed (CBW) includes parts of six states in the Mid-Atlantic region and is home to more than 18 million people. Since the middle of the twentieth century, human activities such as livestock and crop production, urban development, and stream alteration have resulted in nutrients and sediment excess in waterbodies throughout the watershed, causing water quality impairment, freshwater ecosystems’ degradation, and loss of recreational values. To address these issues, the Chesapeake Bay Program (CBP) partnership has coordinated restoration efforts since 1984 [9]. During the last decade, these efforts have been guided by the Chesapeake Bay Total Maximum Daily Load (TMDL), which established limits to nutrients and sediment loadings. The TMDL has been used to formulate comprehensive restoration plans known as Watershed Implementation Plans (WIPs) and outline major

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Abstracts Submitted from MSU:

Abstract 1

Toscano, G. A. P. Nejadhashemi, K. Deb, H. Razavi. L. Linker, 2024. **Advancing Watershed Management: A Multiobjective Optimization and Multicriteria Decision-Making Platform.** iEMSs 2024 Biennial Conference. East Lansing, USA.

Abstract 2

Deb, K., Lu, Z., Kropp, I., Hernandez-Suarez, S., Hussein, R., Miller, S. and Nejadhashemi, A. P., 2024, *Reliable Decision-making Under Uncertainty in Hierarchical Multi-Criterion Problems*, iEMSs 2024 Biennial Conference. East Lansing, USA.

Abstract 3

Deb, K., Goodman, E., and Chikumbo, O. 2024, Multi-objective Land Use Management and Decision-making, iEMSs 2024 Biennial Conference. East Lansing, USA.

Abstract 4

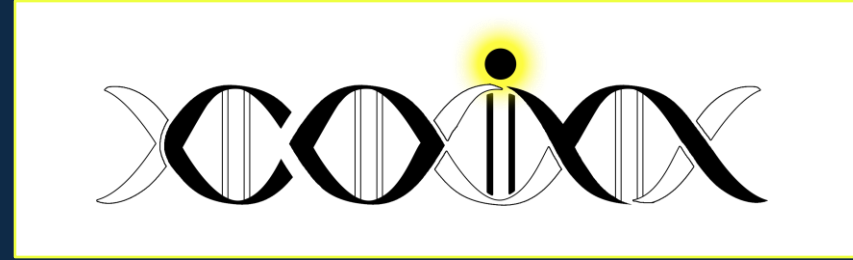
H. Razavi. A. P. Nejadhashemi, K. Deb, Toscano, G. L. Linker, 2024. **Water Resources Management: A Comprehensive Analysis of Elements, Interconnections, and Emerging Synergies.** iEMSs 2024 Biennial Conference. East Lansing, USA.

Abstract 5

H. Razavi. , G. L. Toscano, A. P. Nejadhashemi, K. Deb, Linker, 2024. **Innovative Ranking Methods for Parameter Size Reduction in Large Scale Multi-Objective Optimization Problem.** iEMSs 2024 Biennial Conference. East Lansing, USA.

NEXT STEPS

- Using artificial intelligence to enhance optimization
- Parallel computing platform for faster execution
- Workshops with CBP users for feedback and improvement of our approaches



Computational Optimization and Innovation

Thank you

