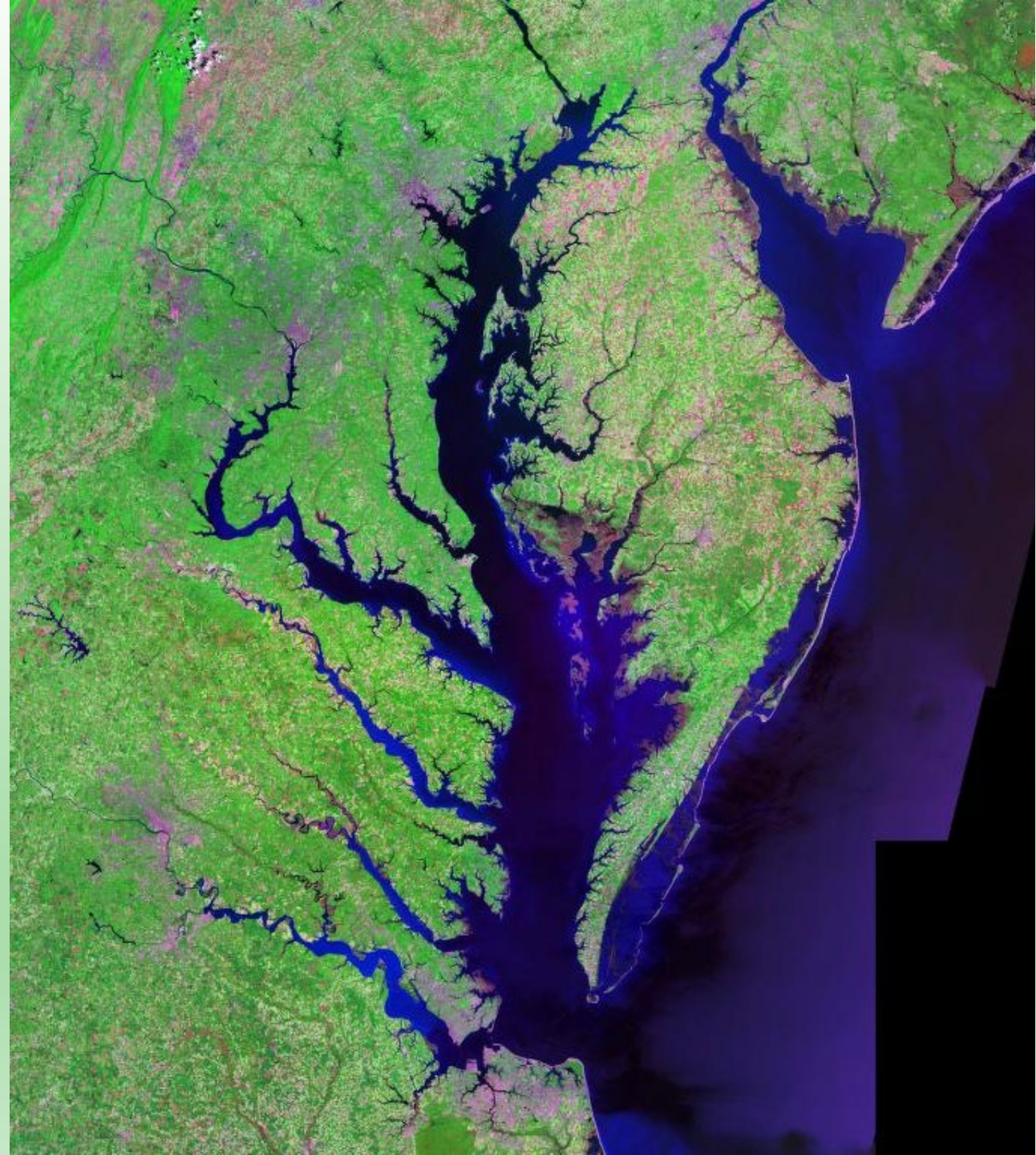


Modeling Workgroup Meeting Quarterly Review
October 2023

Optimization Update

Pouyan Nejadhashemi,
Kalyanmoy Deb, Gregorio
Toscano, and Hoda Razavi

MICHIGAN STATE UNIVERSITY



AGENDA

1	Timeline
2	Overview
3	Reoptimization-validation WV
4	Examining “innovization” strategies beyond WV: Virginia
5	Multi-criteria decision-making
6	Next steps
7	2024 Chesapeake Bay Optimization Webinars

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 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



*Timeline of
the Project*

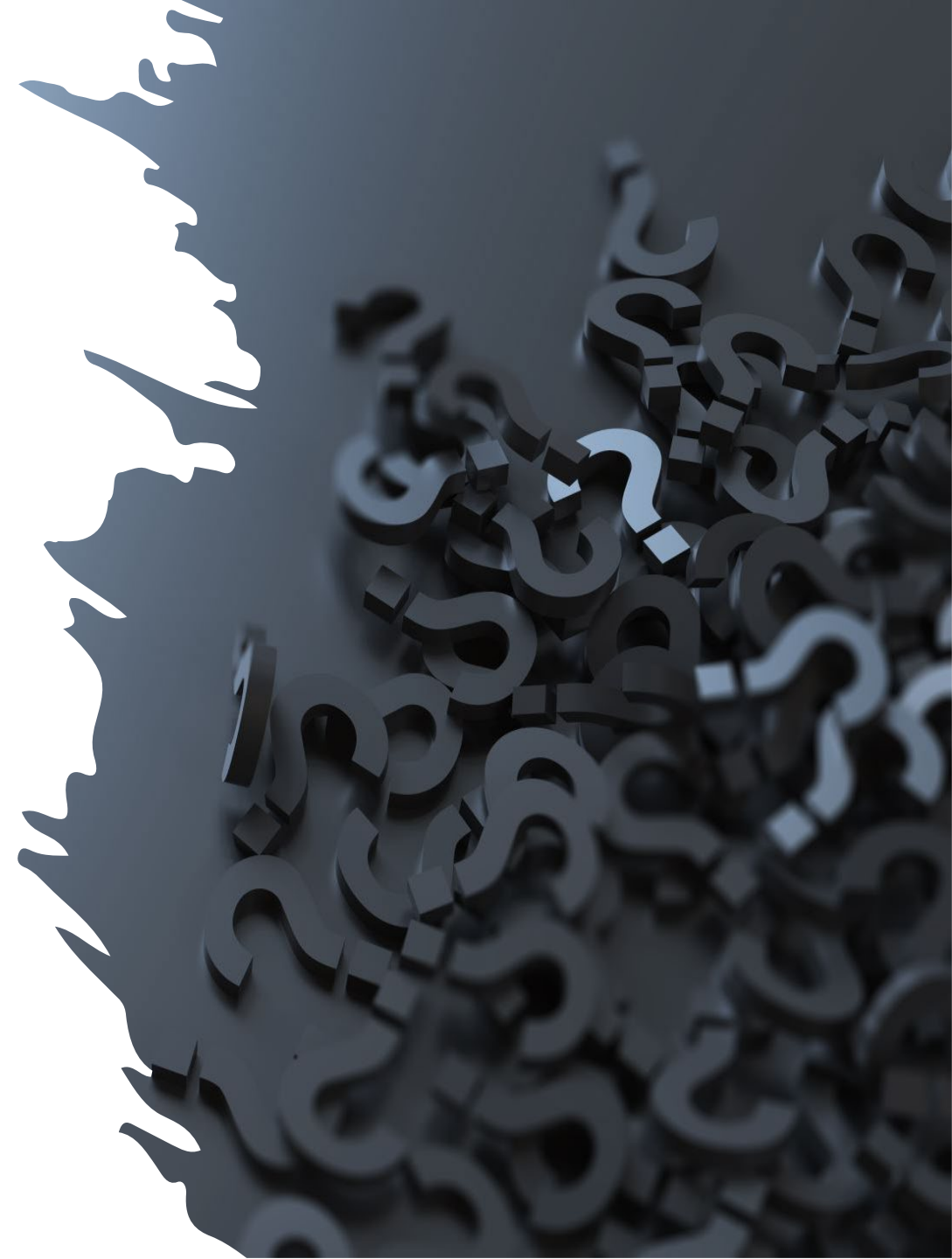


OVERVIEW



Problem Statement

One of the most challenging issues for a real-world optimization problem is the **Search Space Complexity** (variables and constraints), especially for the CBW management problem.



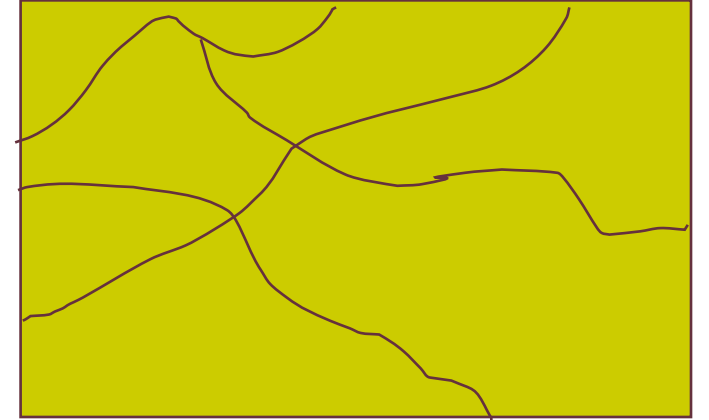
Problem Significance (Search Space Complexity)

- Each county on average has 10 land-river segments,
- Each landriver segment can accept up to 200 BMPs options
- Each landriver segment has 50 land use options
- Making the overall search space for a county to have about $(50 * 200)^{10} = 10^{40}$ solutions.
- Highly constrained: ~100 000 constraints.
- High-dimensional: more than 2 million variables at the watershed level



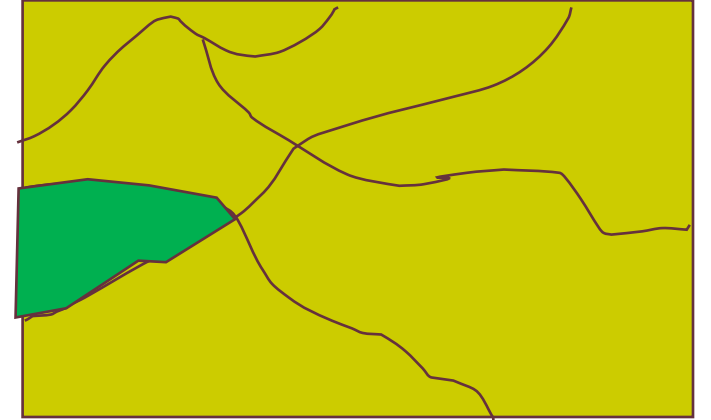
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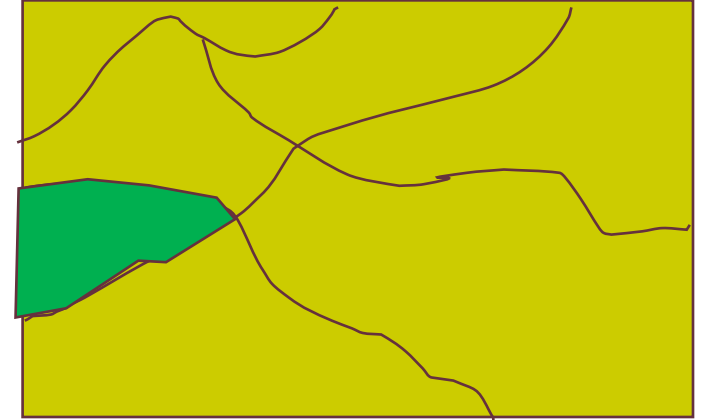
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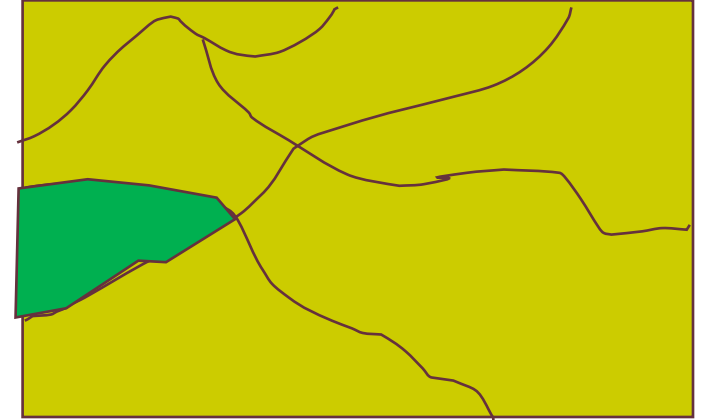
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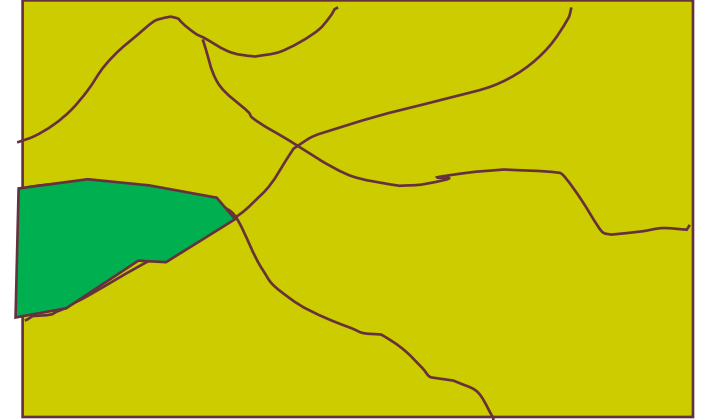
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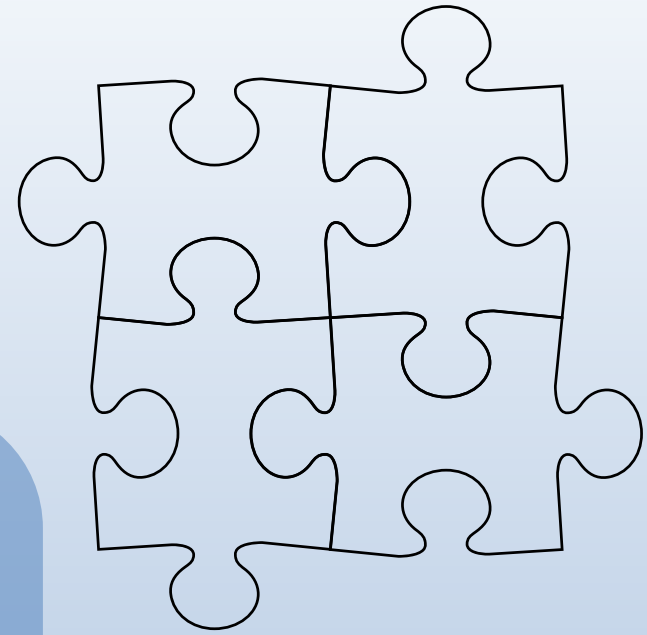
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Thousands of BMP implementation scenarios can be evaluated and compared.

Beating the "Curse of Dimensionality"

- ❑ Due to the **large dimension of the problem**, there is **no off-the-shelf optimization algorithm** capable of handling this problem.
- ❑ Therefore, we developed a **customized optimization** approach **to speed up computational time and reduce the size of optimization variables** to make the problem solvable in a reasonable time frame.



Proposed Solution Approach



1. Employ an **Initial Local Search** on a Math Model (for efficient BMPs only)

to reduce the computational time associated with running watershed model (Discussed in previous presentations using IPOPT)

2. Employ a **Multi-obj. Optimization** algorithm using CAST

to find a number of trade-off Pareto solutions (Discussed in previous presentations)

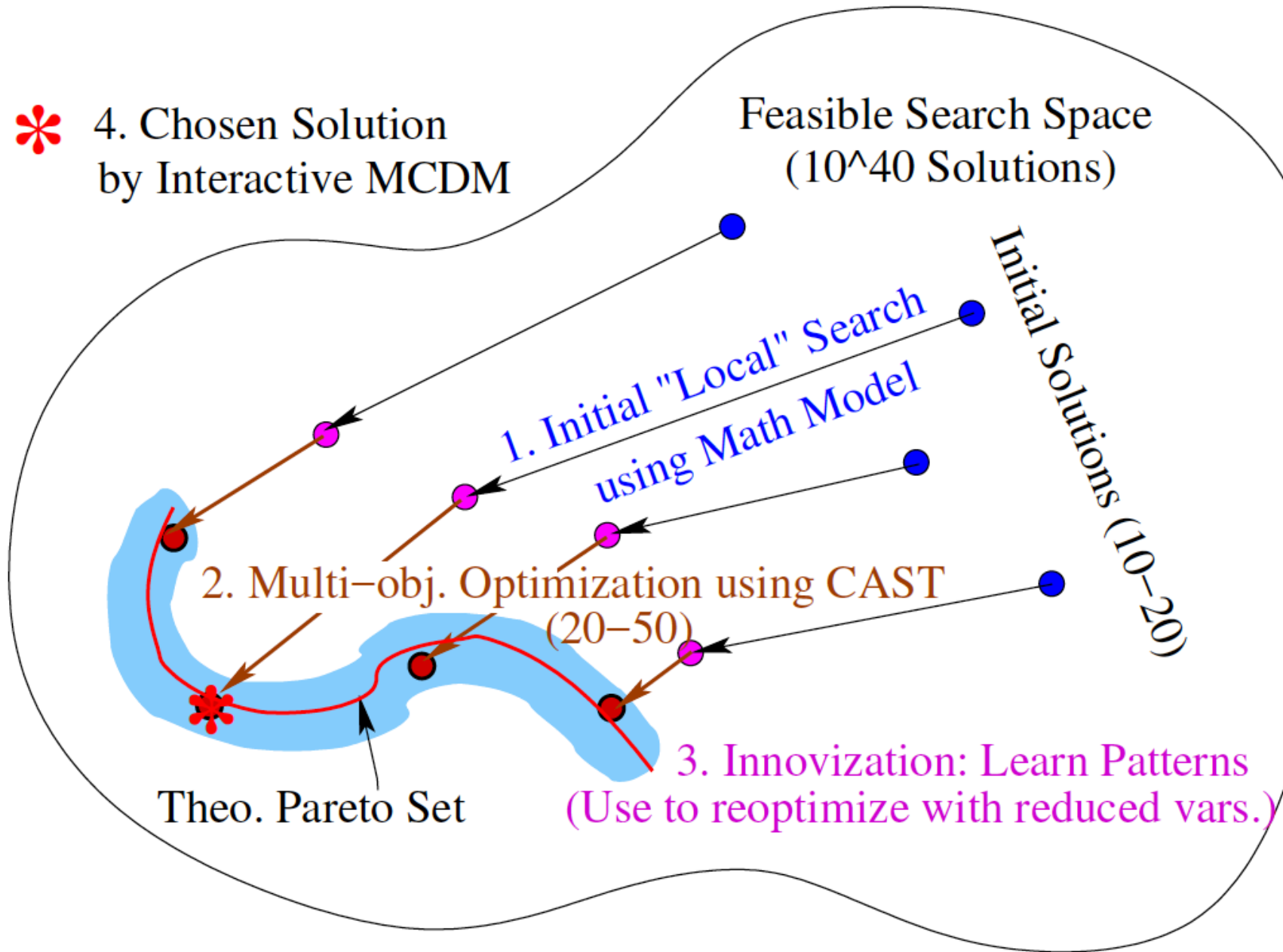
3. **Innovization: Learning Patterns**

to learn patterns from Pareto solutions for re-optimization with reduced number of variables (Discussed here)

4. **Multi-Criterion Decision-making (MCDM)**

to choose a single preferred solution (Discussed here)

Overall Approach



Innovation through Optimization

The major problem we are facing is **the large number of optimization variables**. These variables originate from three major components:

- Type of BMPs
- BMP implementation location
- Size of BMPs



Innovization

By understanding **the common characteristics of the group of BMPs or locations of implementation**, we can reduce the number of BMPs and ultimately **reduce the total number of variables**.

Study Area



The number of variables and constraints depends on **the scale of the county or state** under study.



West Virginia



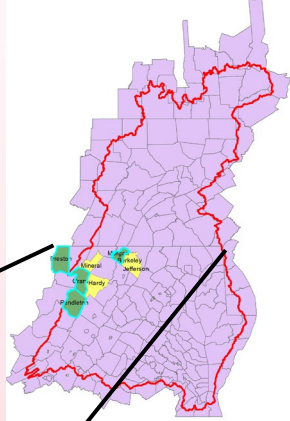
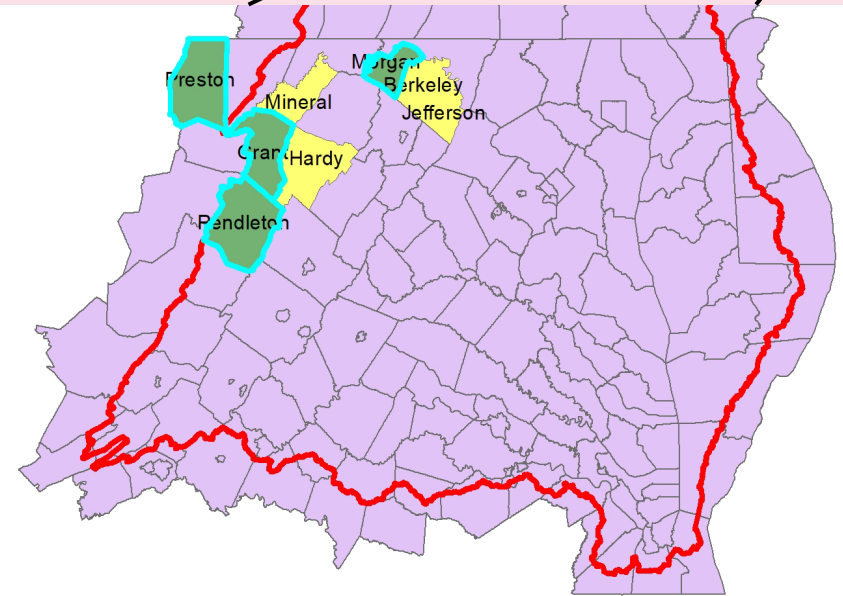
Four county: 65,260 variables (Berkeley, Jefferson, Mineral, and Hardy)



Entire state: the number of variables is about 153,818.

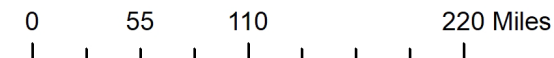


For any optimization algorithm, these numbers are regarded as substantial and computationally challenging.



Legend

- Reoptimization counties
- Counties for original optimization
- Chesapeake_Bay_Watershed_Boundary
- County_Boundaries



Ranking Conservation Practices

Discover the top-rated conservation practices and how to implement them!



Innovization in CPB

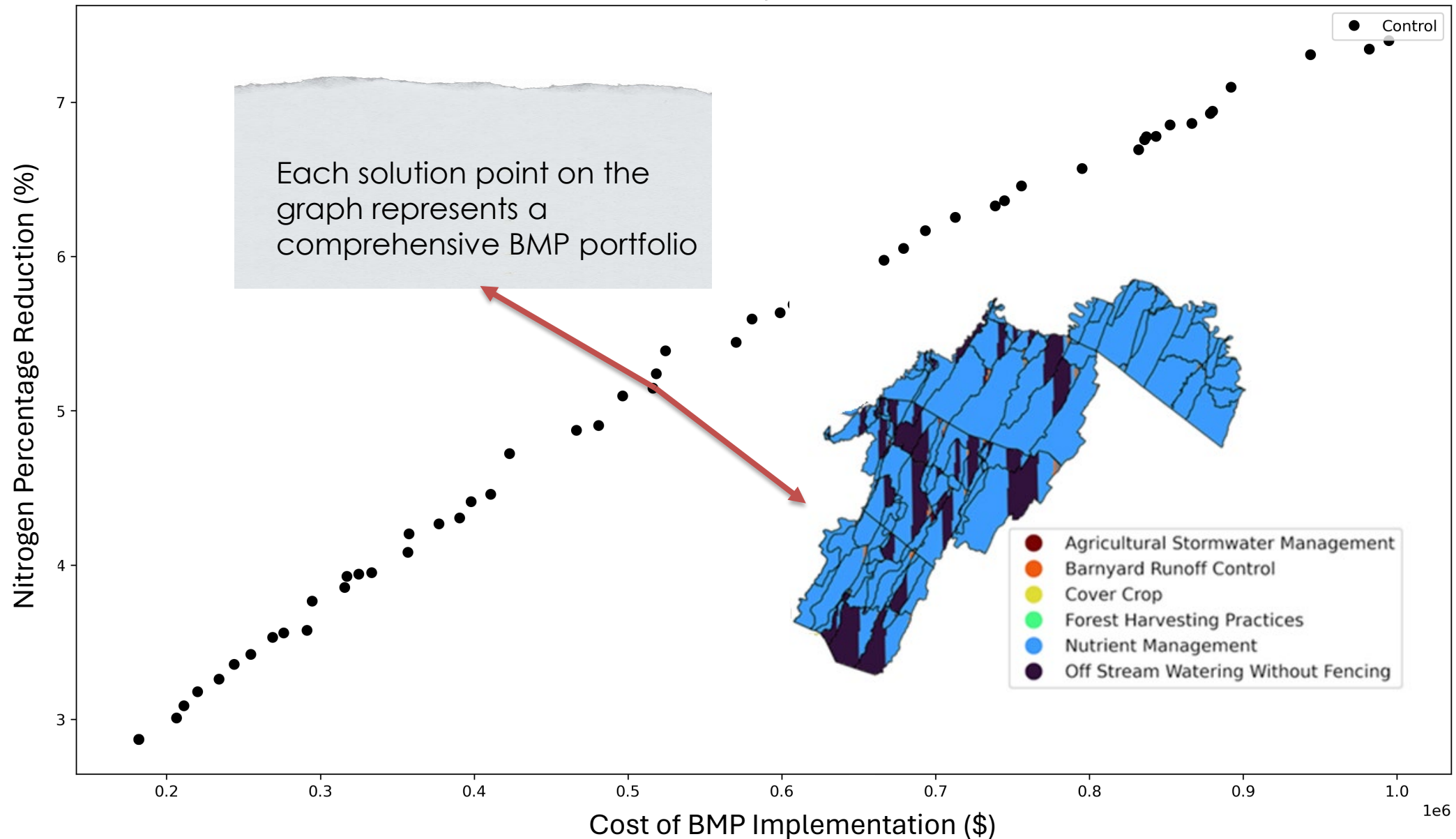
Use different ranking strategies to **identify the top 10 ranked BMPs** by the optimization algorithm.

- implementation acreages
- maximum allowable acreages
- nitrogen reduction per dollar spent

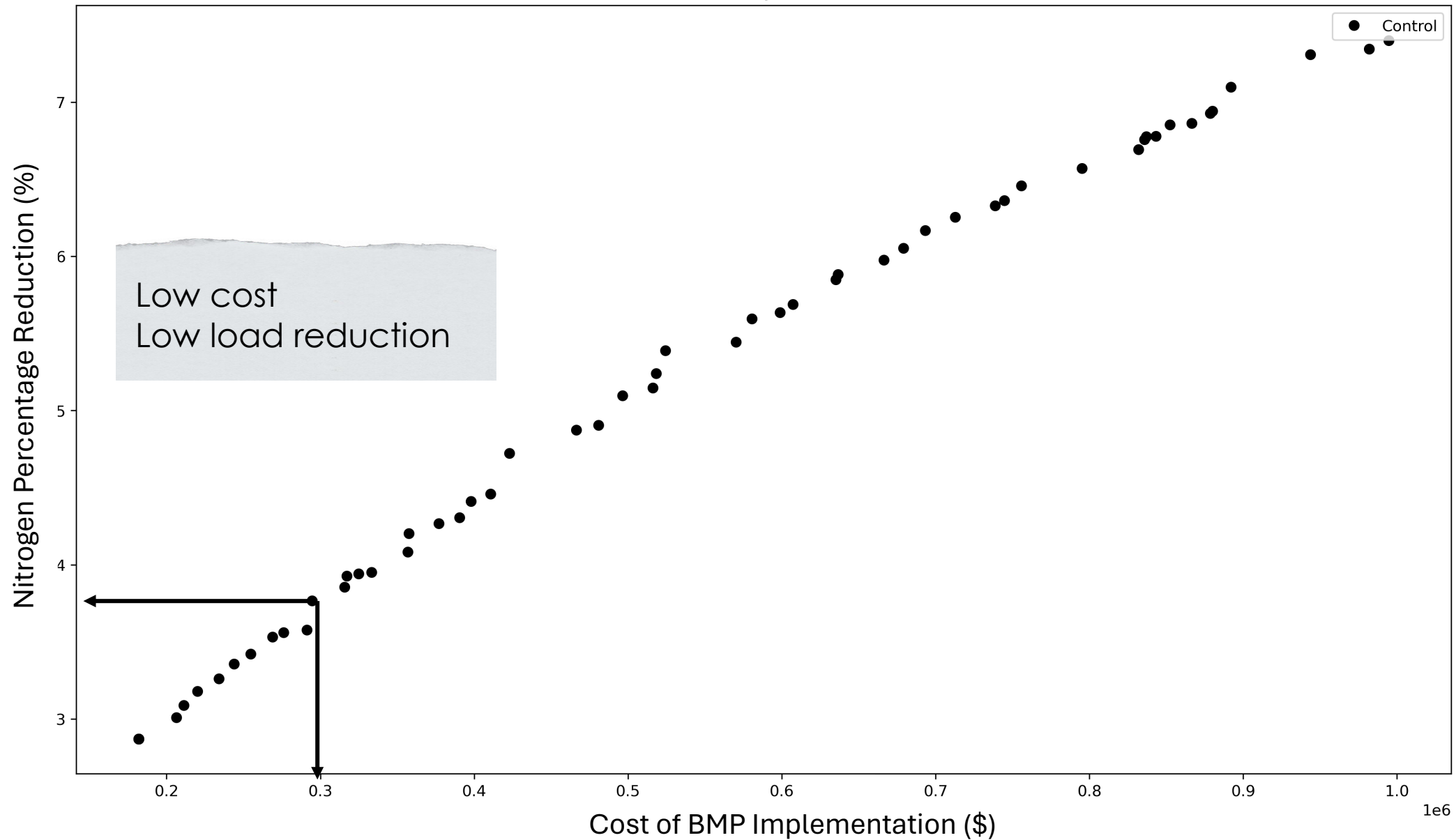
Four counties for the **initial testing** of the **innovization algorithm**: (Berkeley, Mineral, Hardy, and Jefferson) of West Virginia

The results from these new strategies (**top 10 BMPs**) were compared against the **original optimization** algorithm (**200 BMPs**) in these counties.

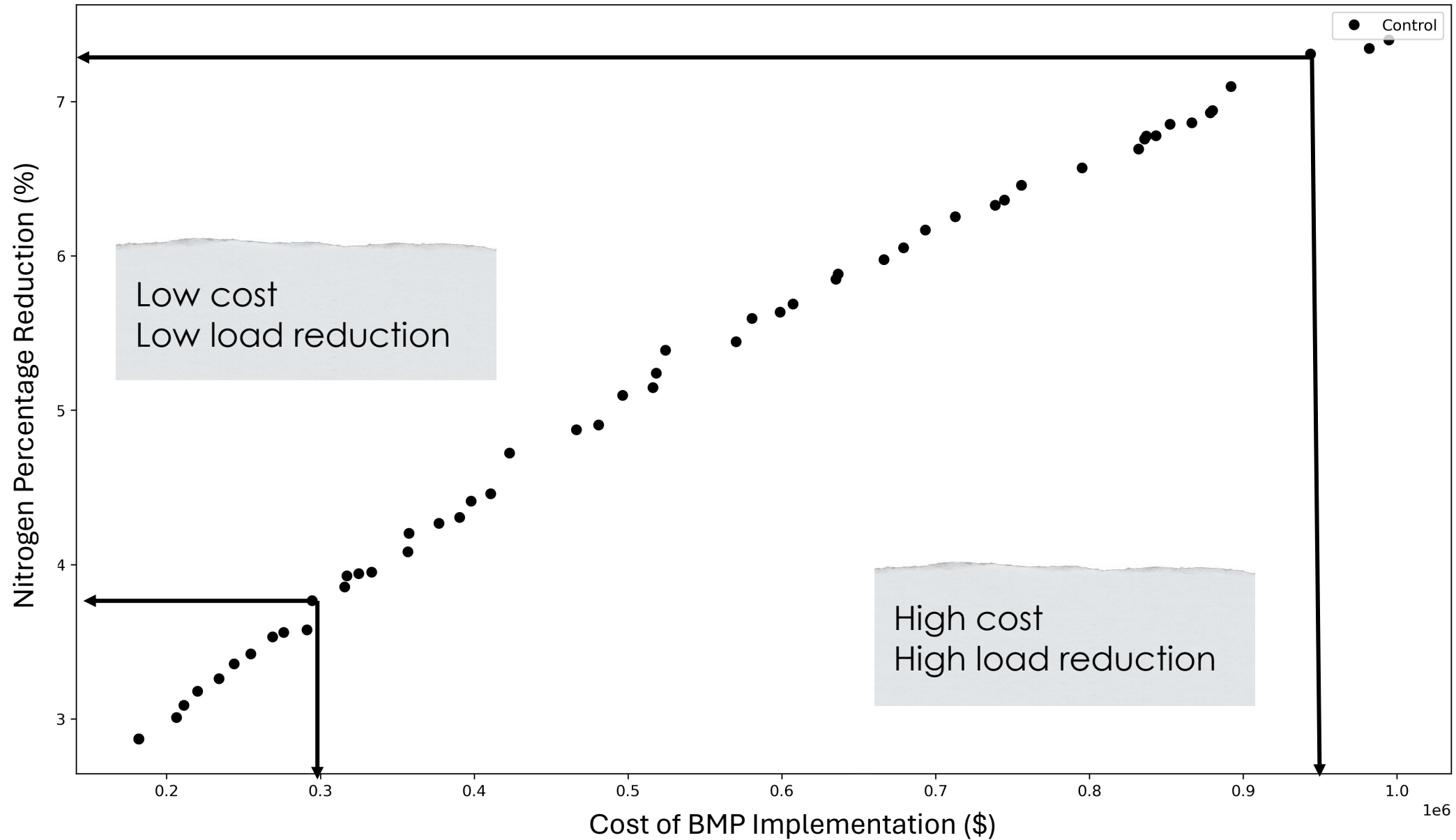
Original Optimization



Original Optimization

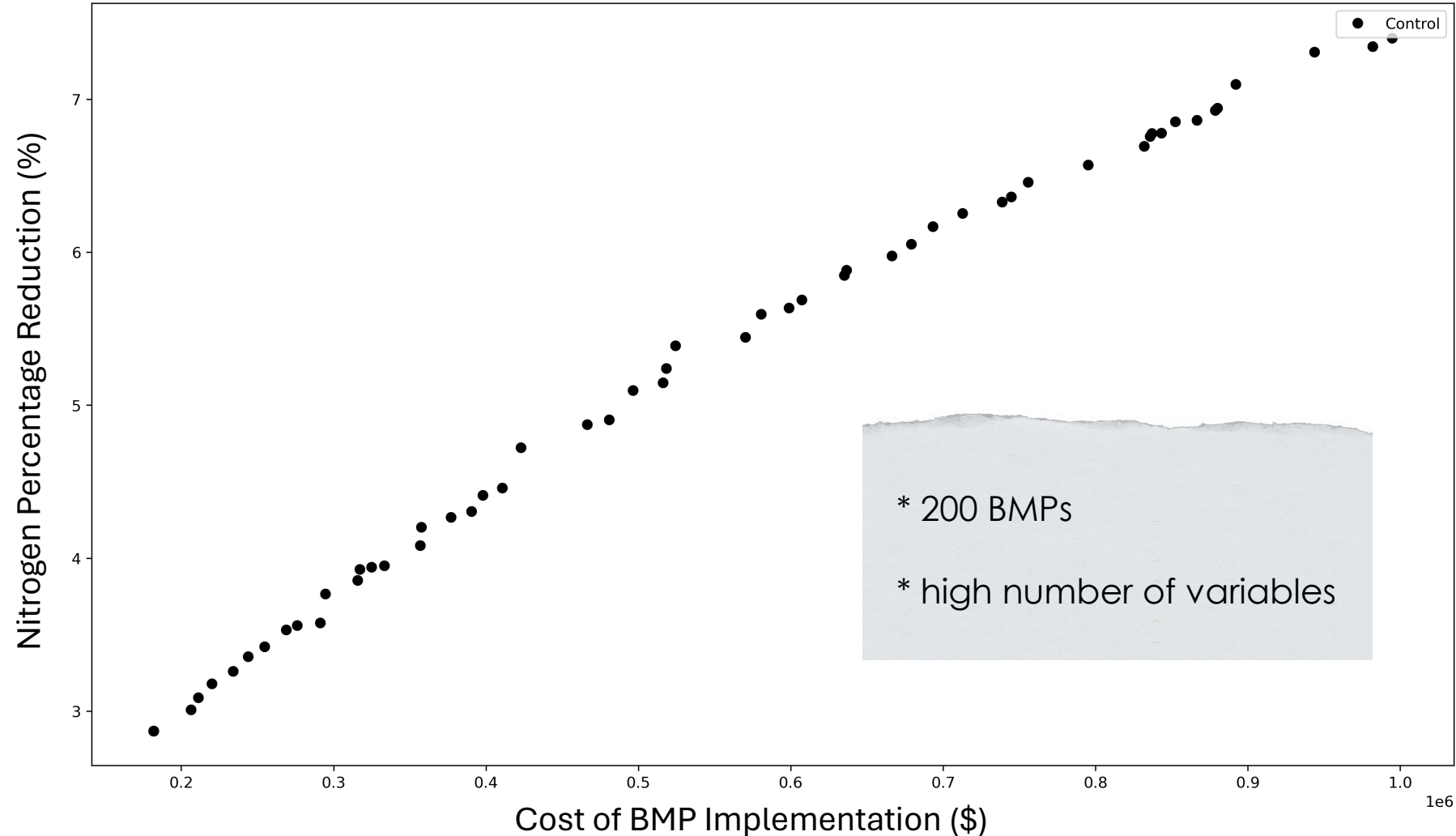


Original Optimization



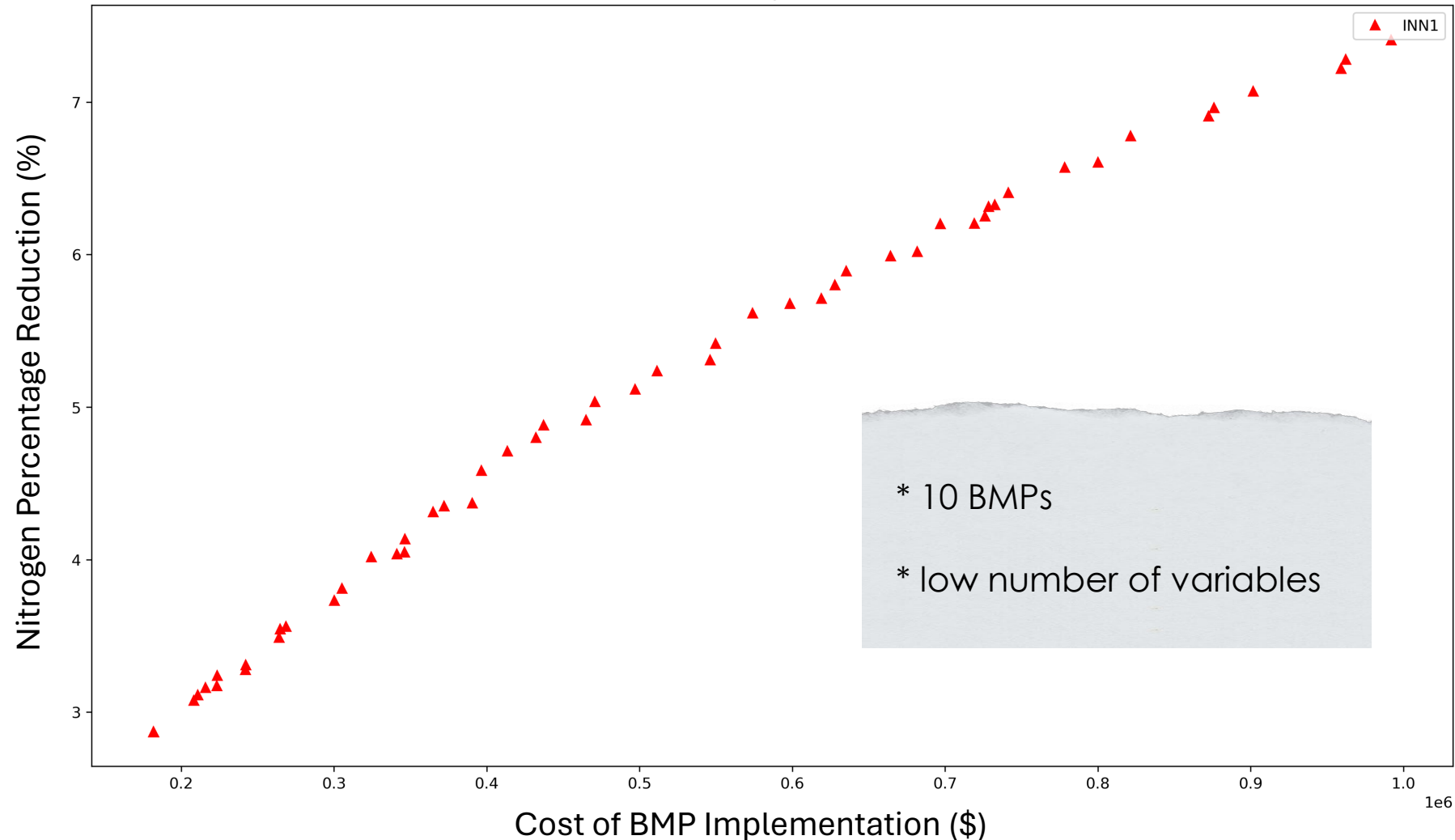
Original Optimization

Berkeley, Hardy, Jefferson, and Mineral Counties



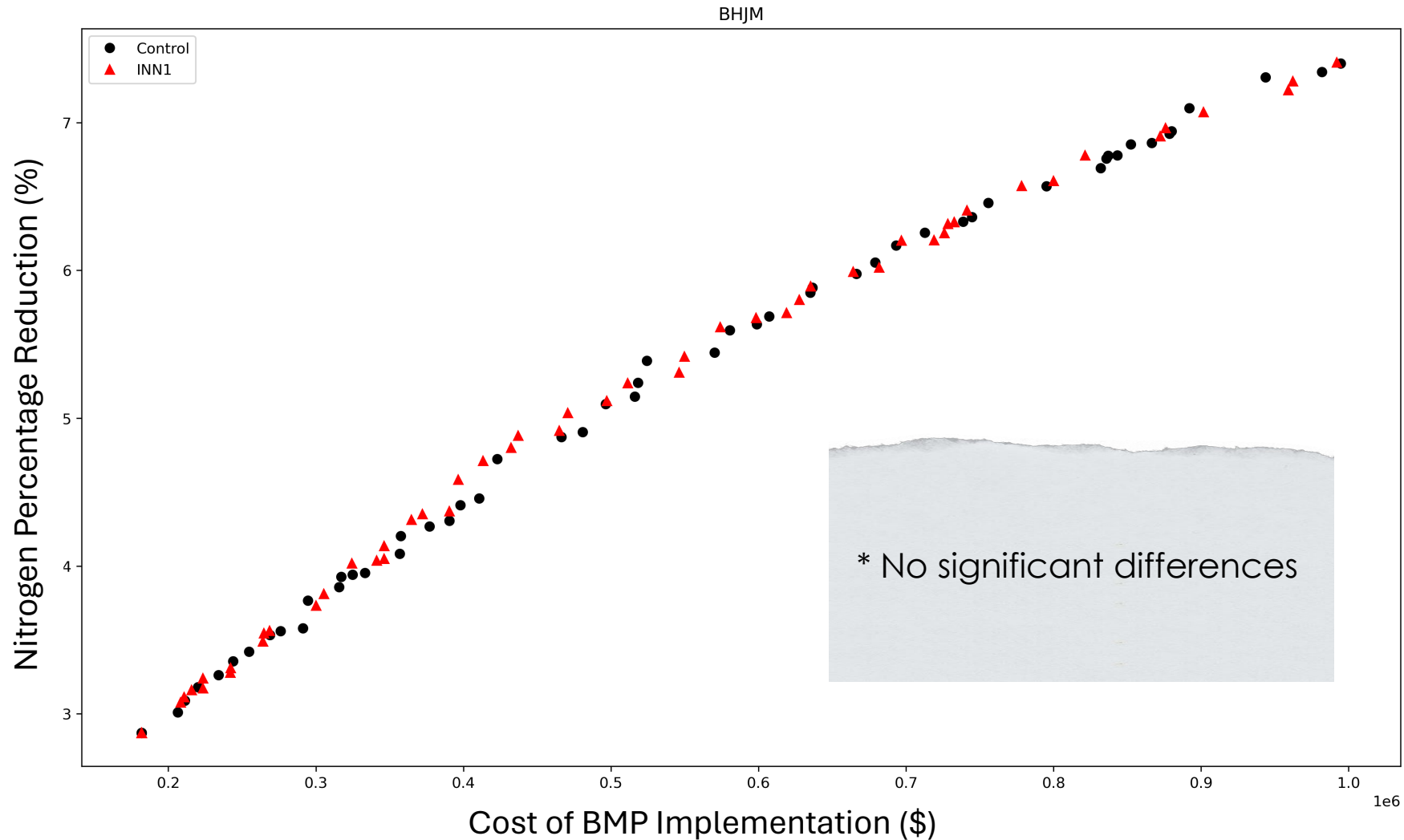
Innovized Optimization

Berkeley, Hardy, Jefferson, and Mineral Counties



Compare Original vs. Innovized Optimization

Berkeley, Hardy, Jefferson, and Mineral Counties



Innovization- for efficiency BMPs-



By reducing the number of BMP from about **200 types of efficient BMPs to only 10 BMPs**, the size of the problem was significantly reduced.



The innovizaed approach can reduce the number of variables by **about 96%**, which is a promising result.



Reoptimization-Validation

Reoptimization



Evaluate the performance of original innovization technique other counties



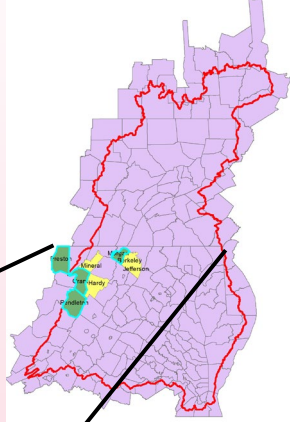
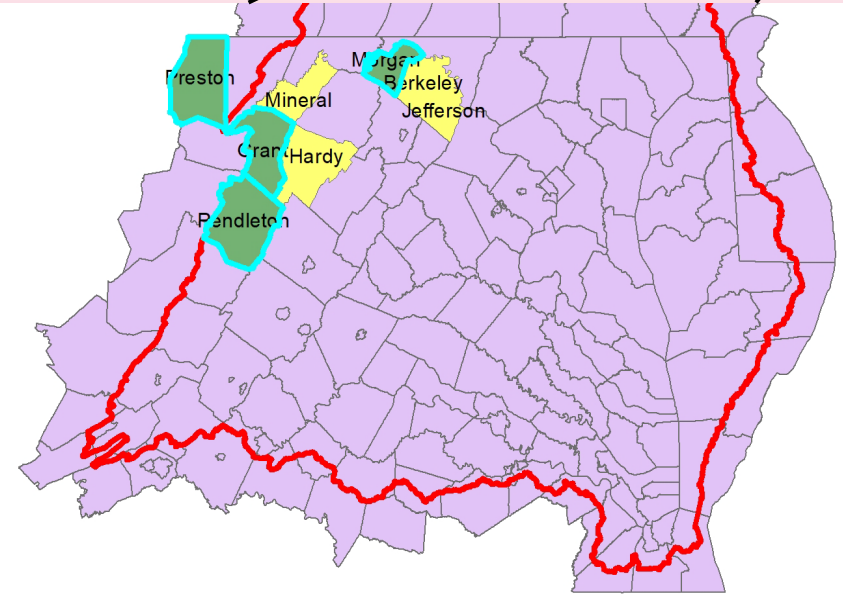
West Virginia



Four counties: 71,661 variables
(Grant, Morgan, Pendleton, and Preston)



The best innovization strategy (10 BMPs) outperforms the control (>200 BMPs).



Legend

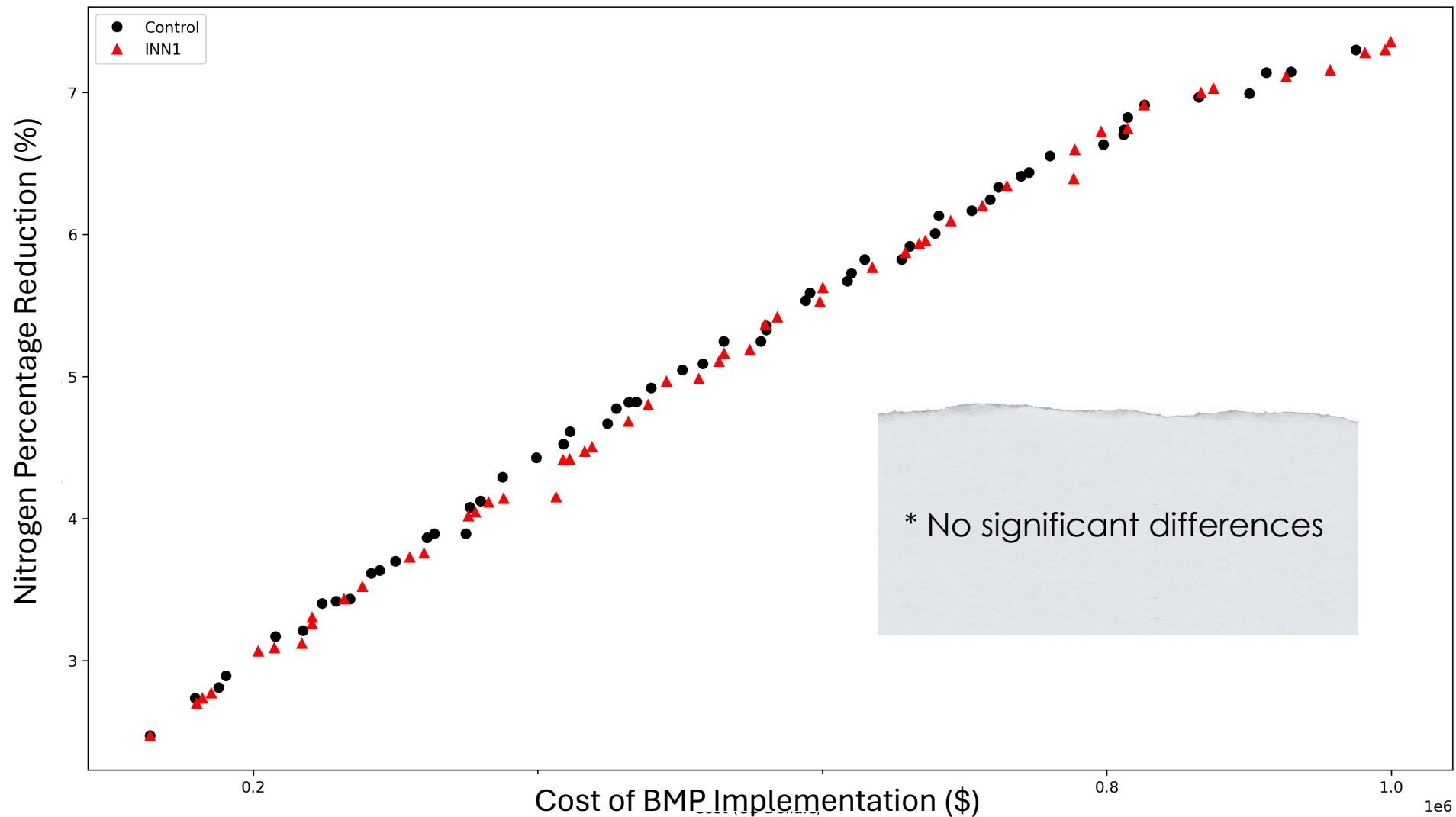
- Reoptimization counties
- Counties for original optimization
- Chesapeake_Bay_Watershed_Boundary
- County_Boundaries

0 55 110 220 Miles

Reoptimization

Compare Original vs. Innovized Optimization

Grant, Morgan, Pendleton, and Preston Counties



Innovization effectiveness

The results of this study show that innovization technique is an effective approach to significantly reducing the size of the optimization problem.

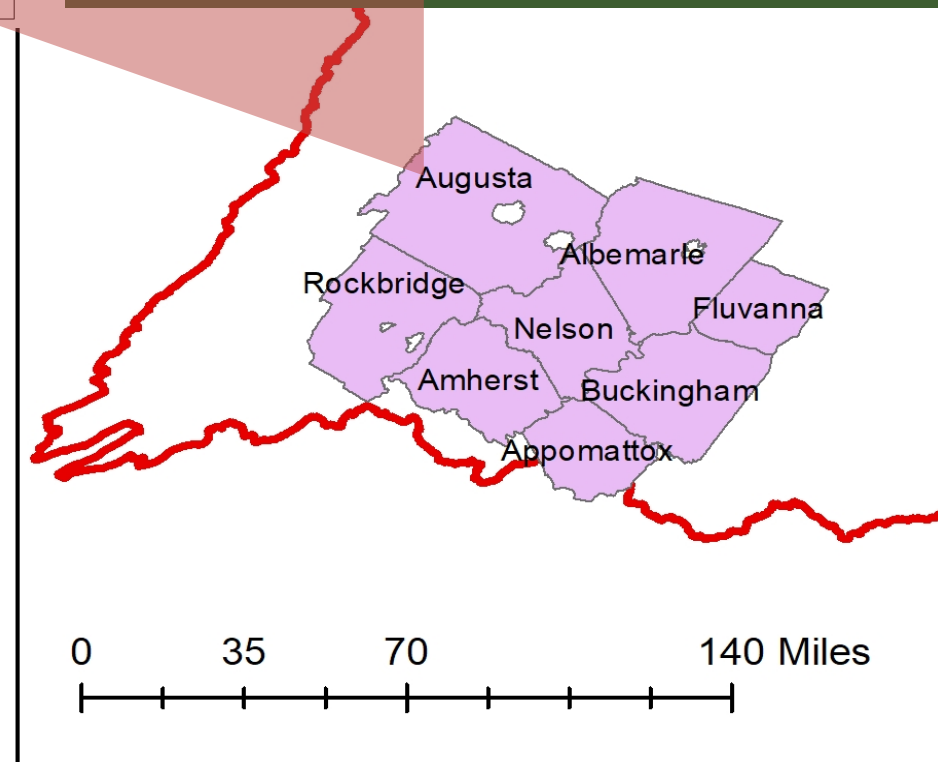
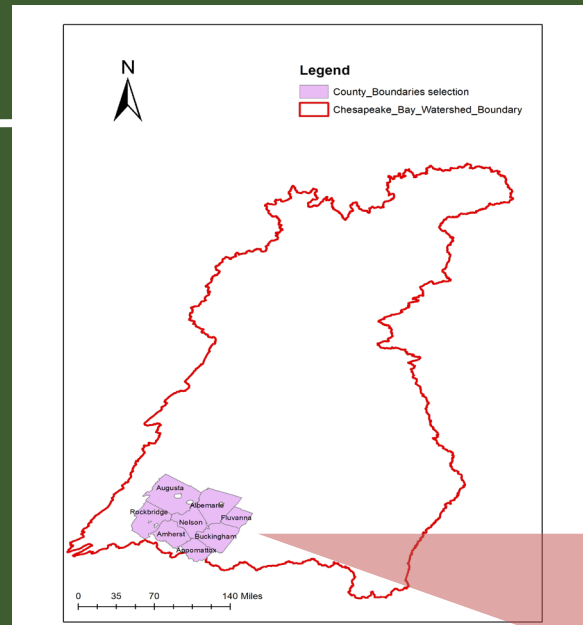
This reduction in variables enhances computational efficiency without sacrificing solution quality

Extract critical knowledge allow for solving similar problems without performing any new optimization.

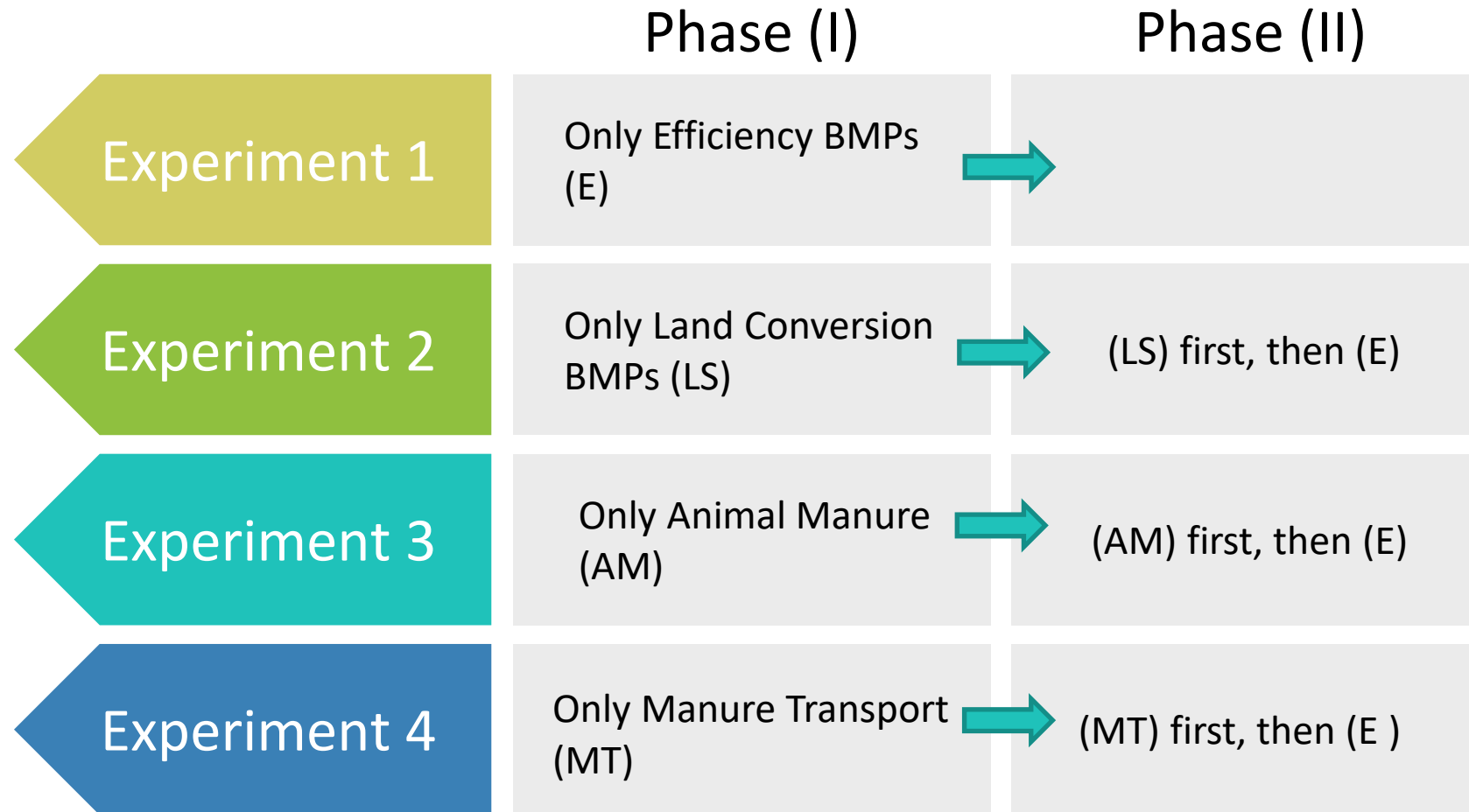


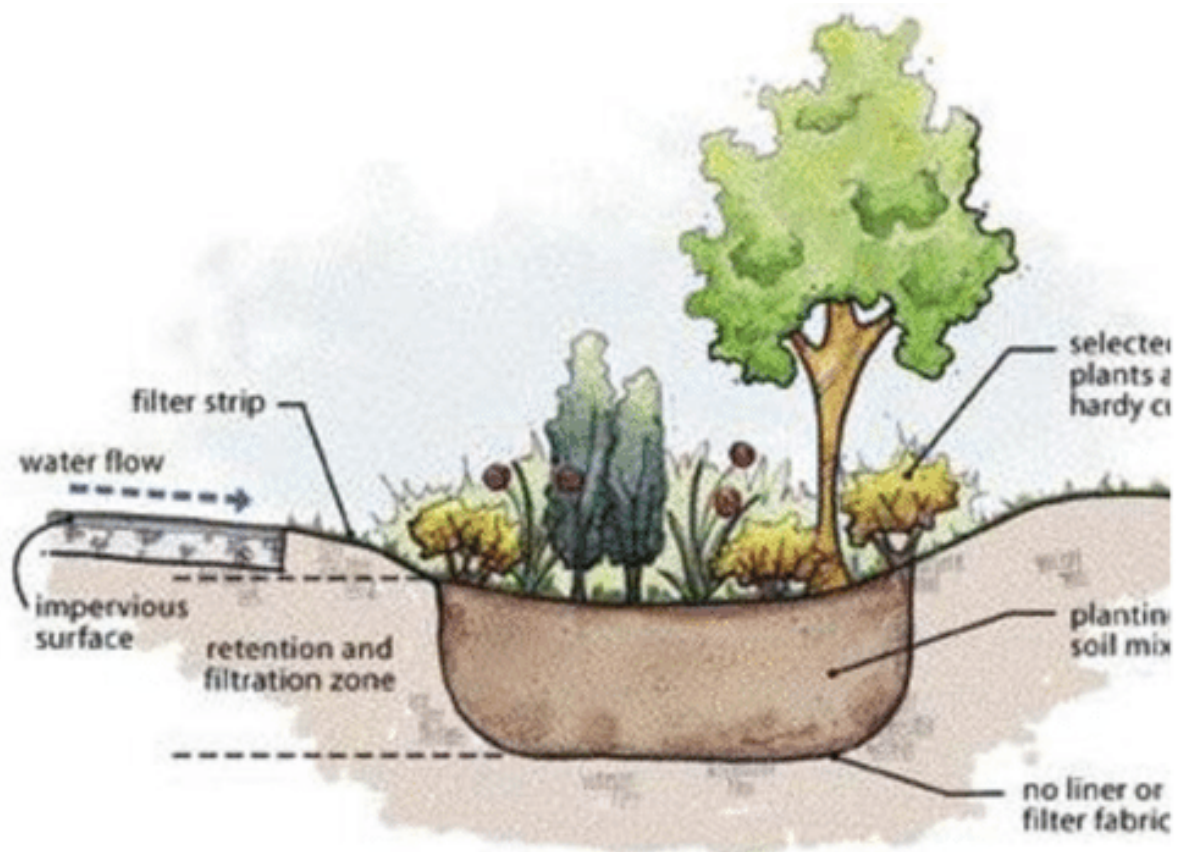
From West Virginia to Virginia: Innovization Strategies

Study Area



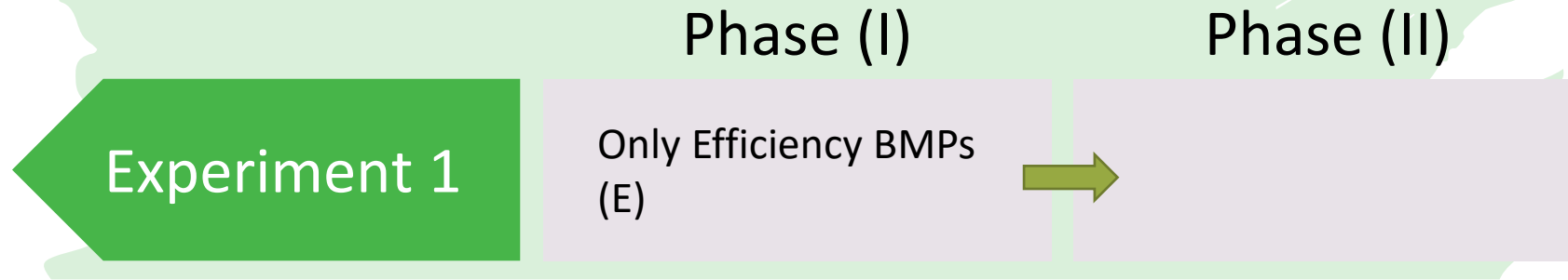
Combinations of Optimization Scenarios

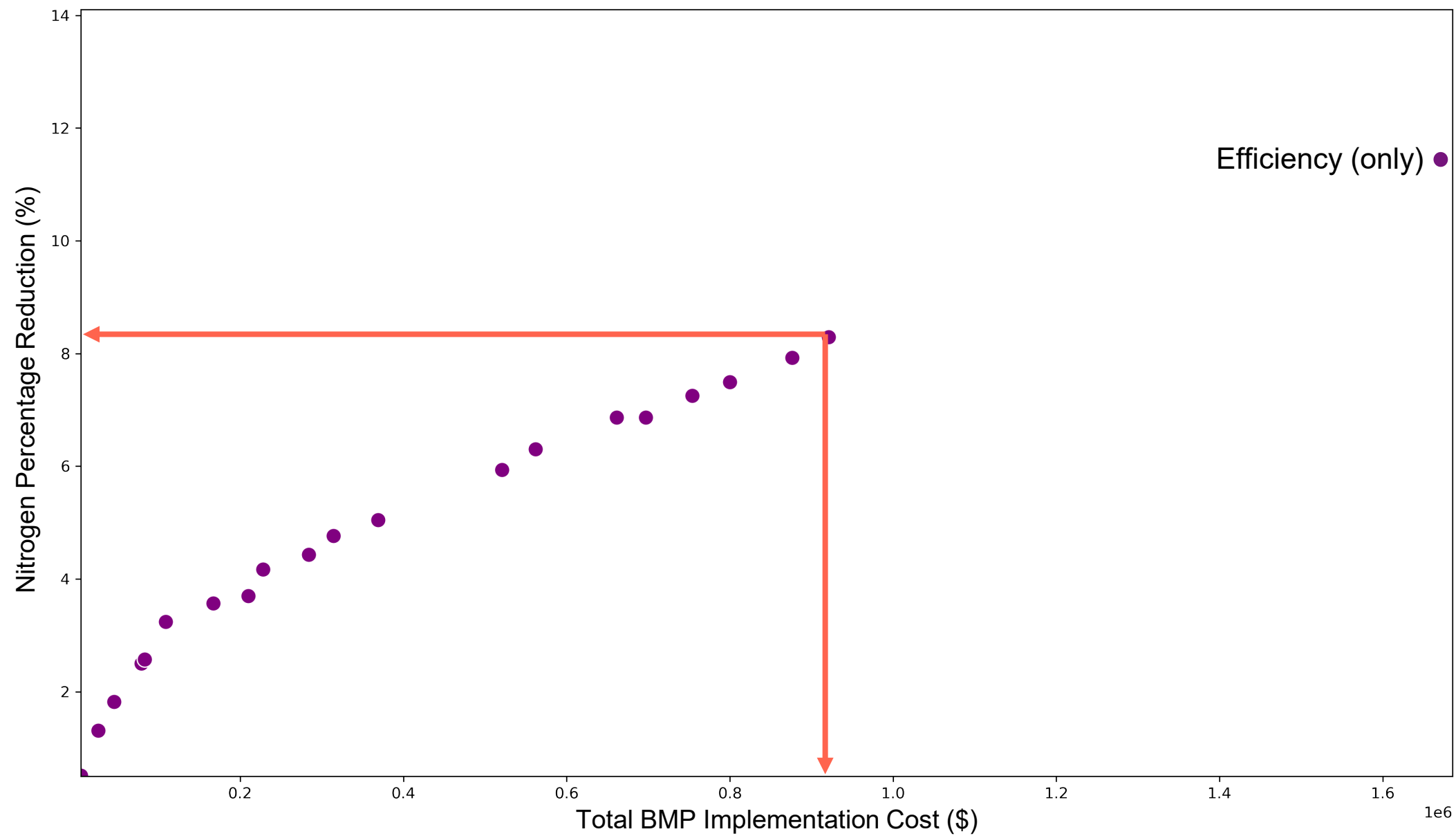




1

Efficiency BMPs (Nelson)

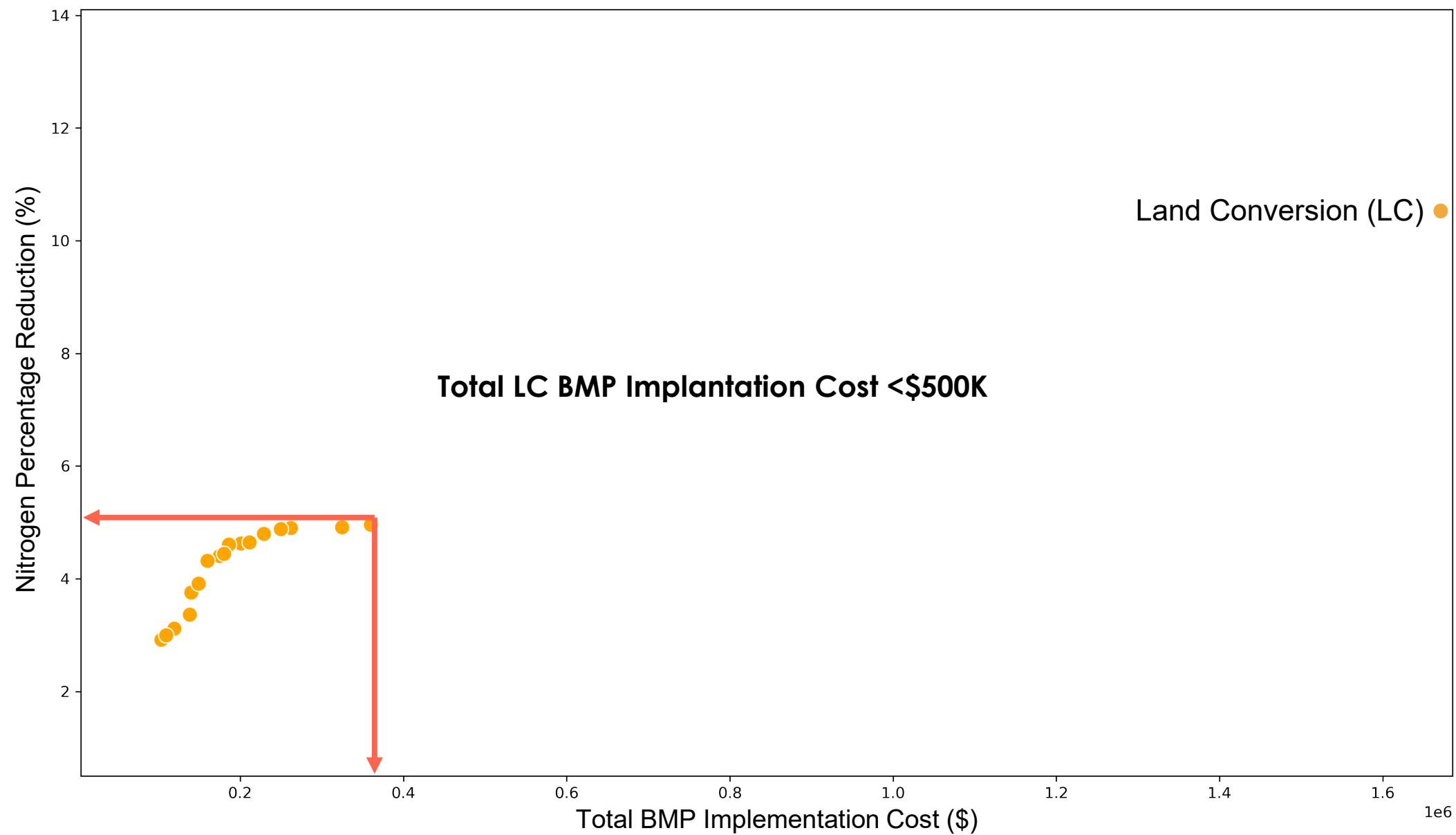




2

Land Conversion BMPs (Nelson)





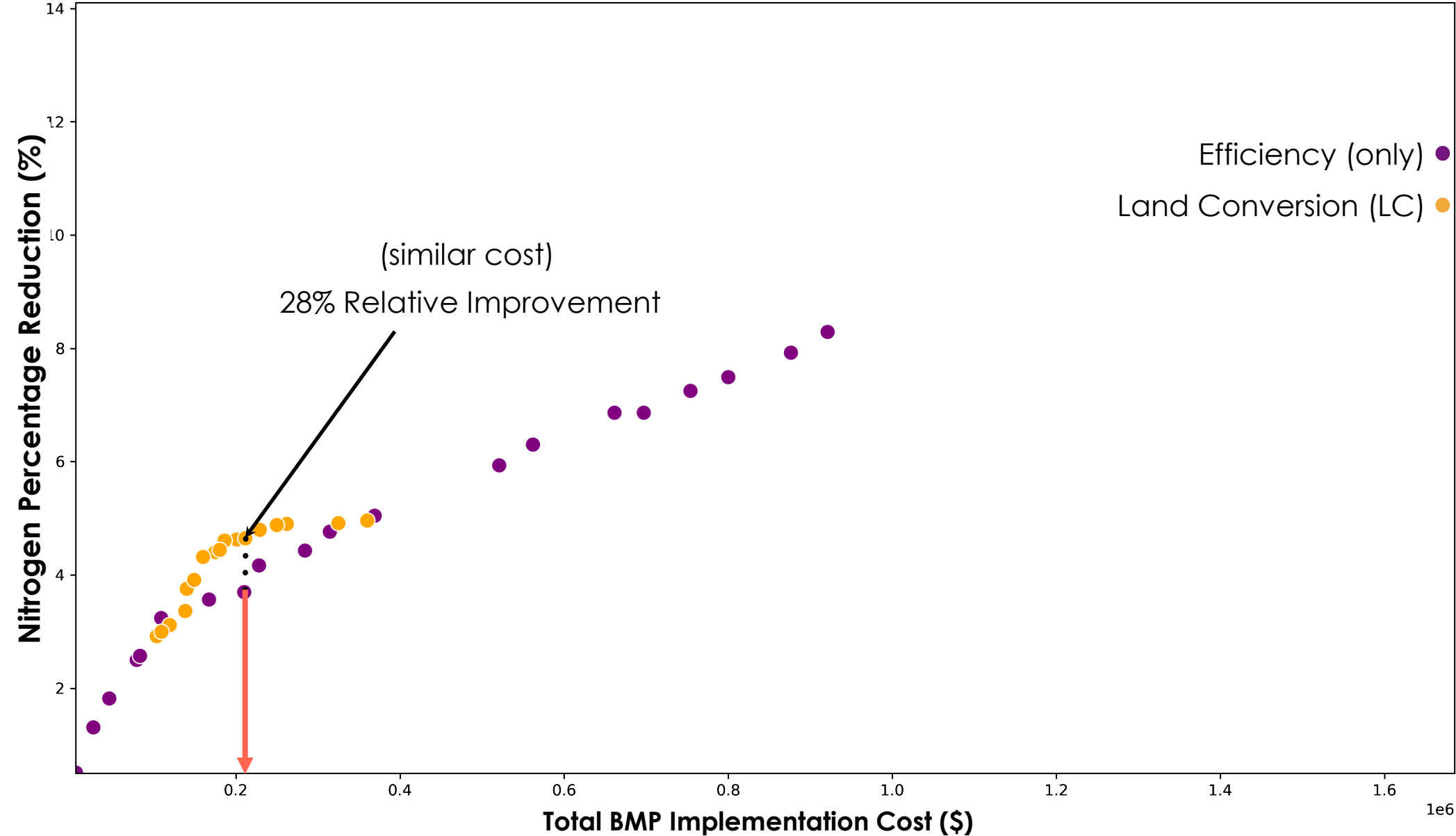
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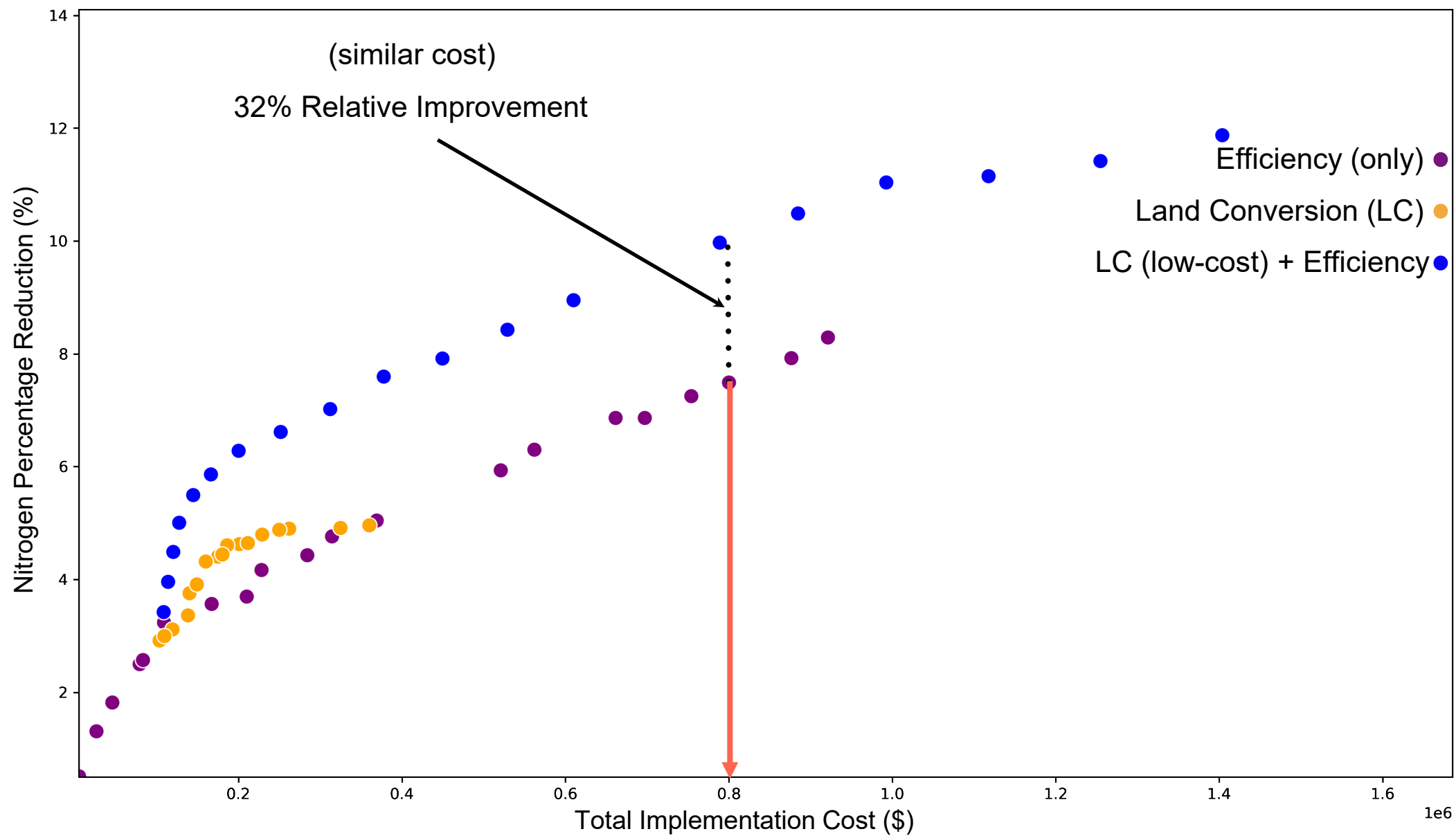
Land Conversion and then Efficiency BMPs (Nelson)

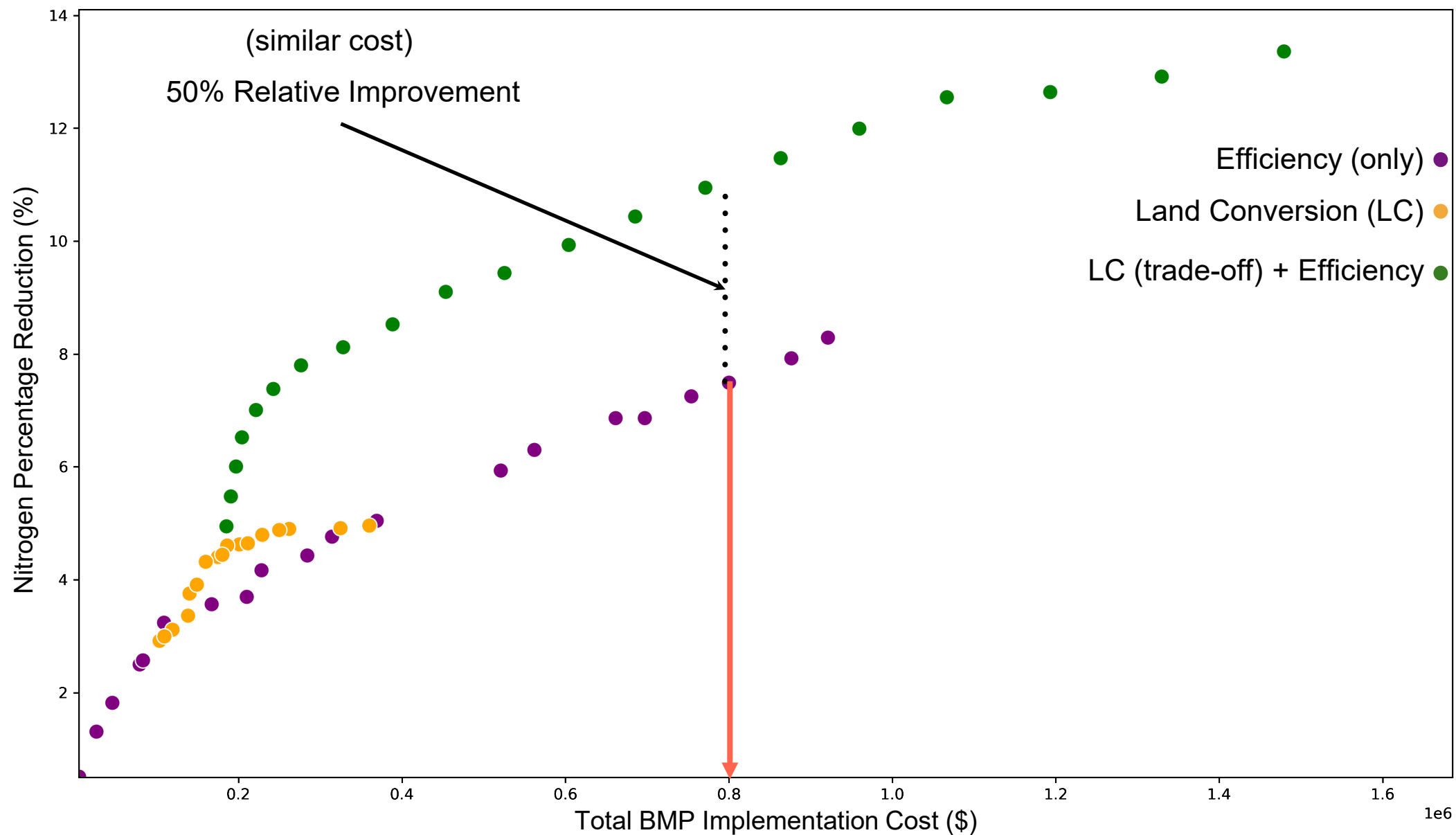


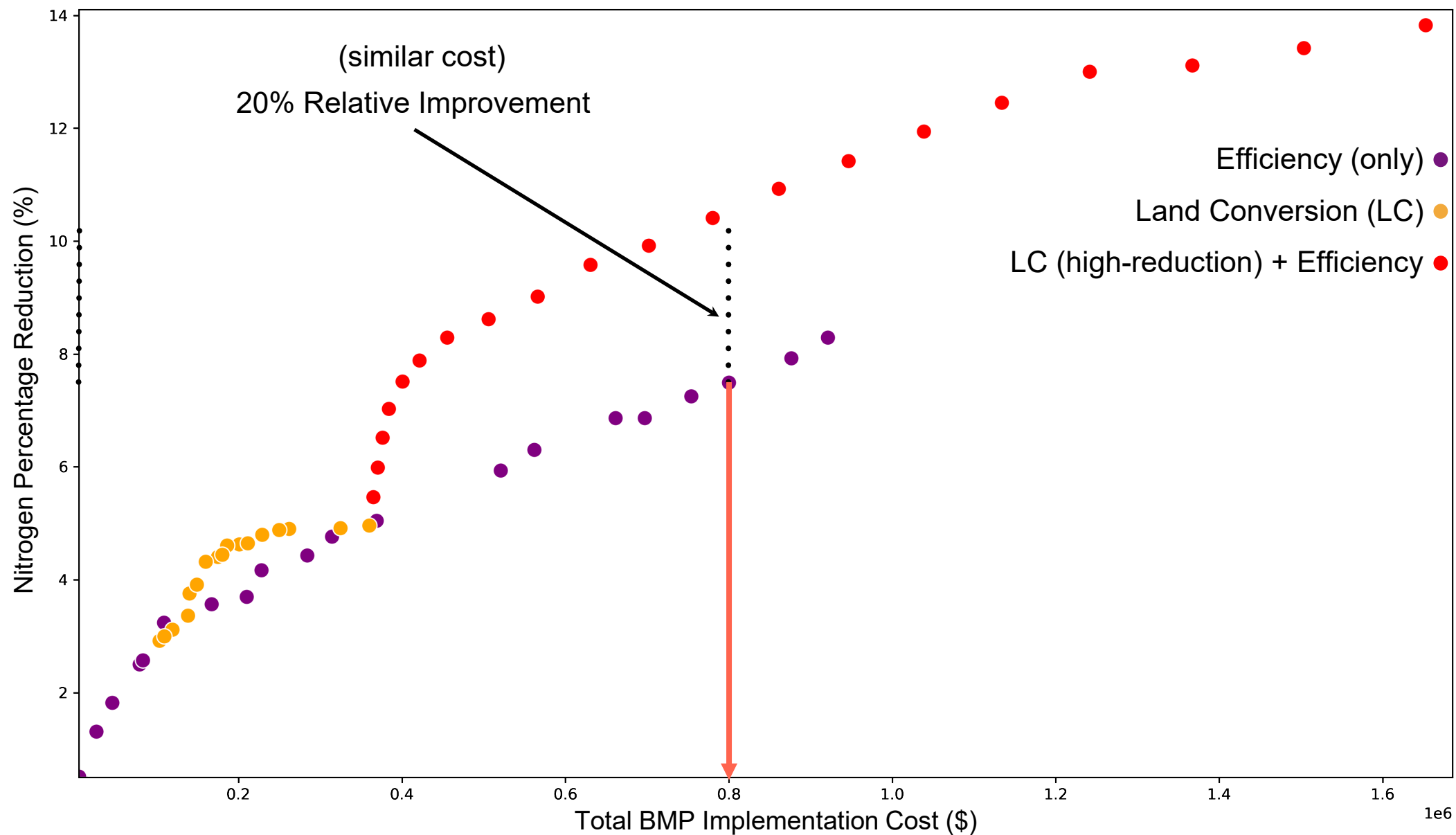
Total LC BMP Implantation Cost <\$500K

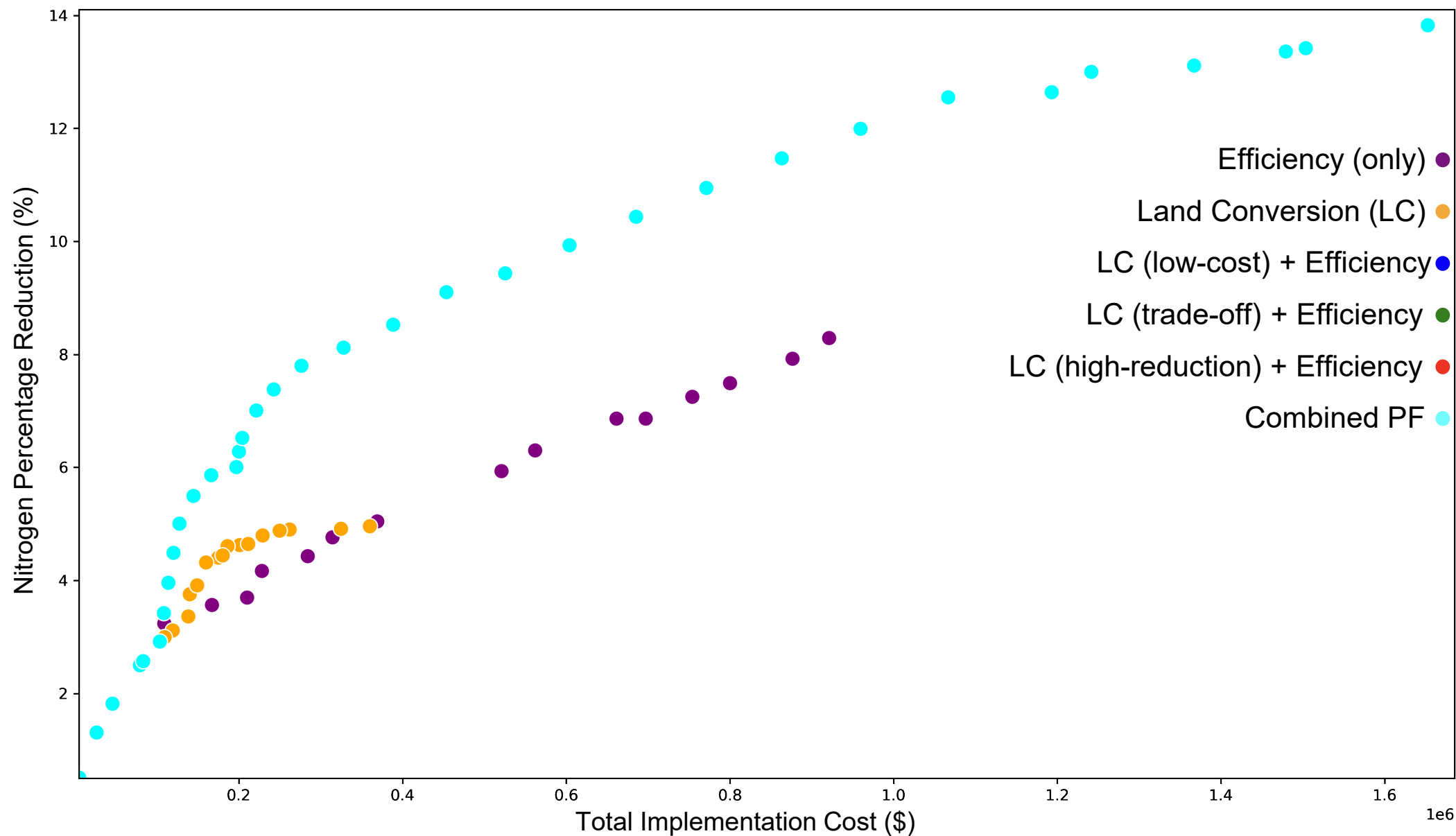
Comparison of optimization solutions from Efficiency and Land conversion BMPs











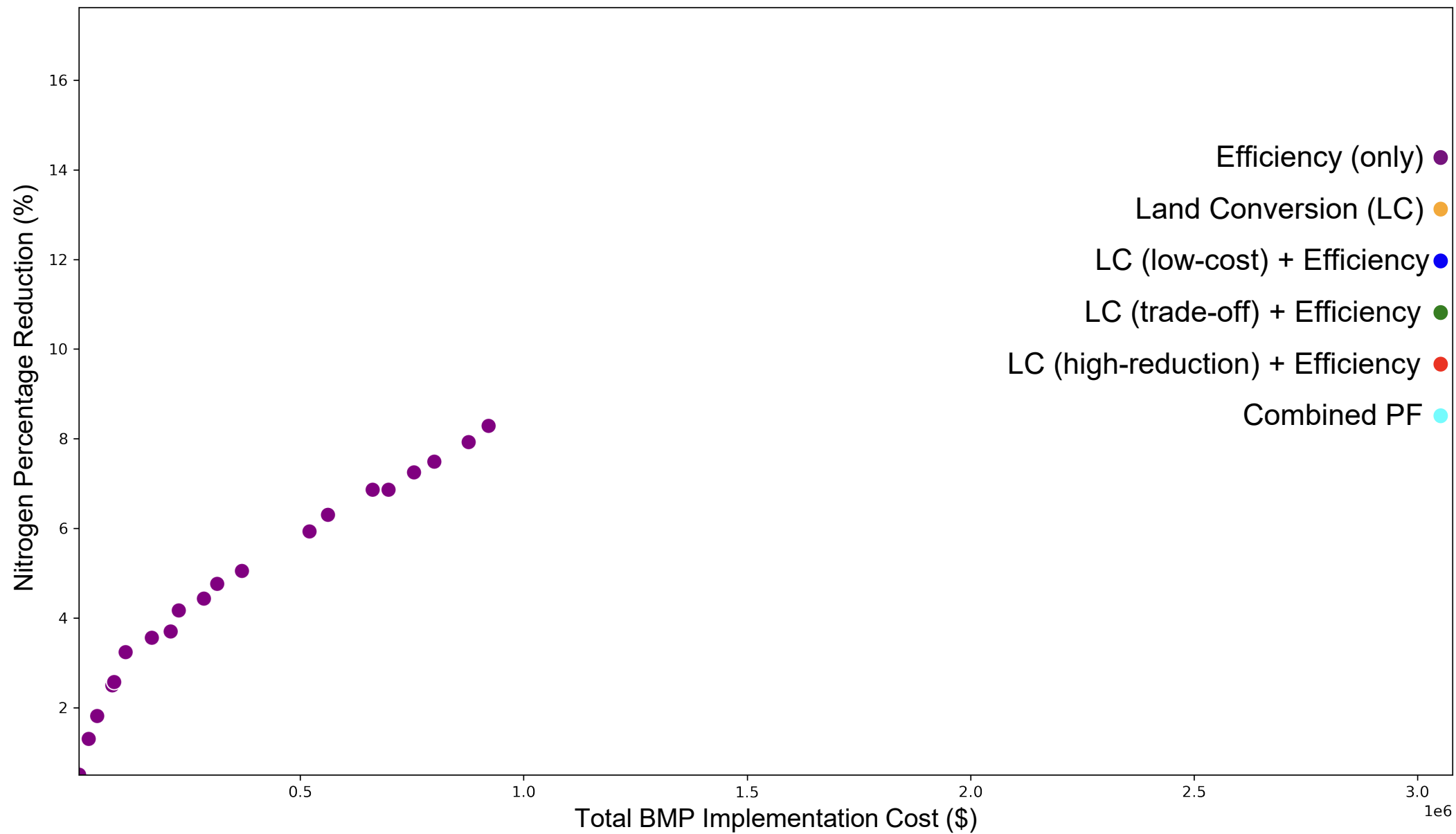


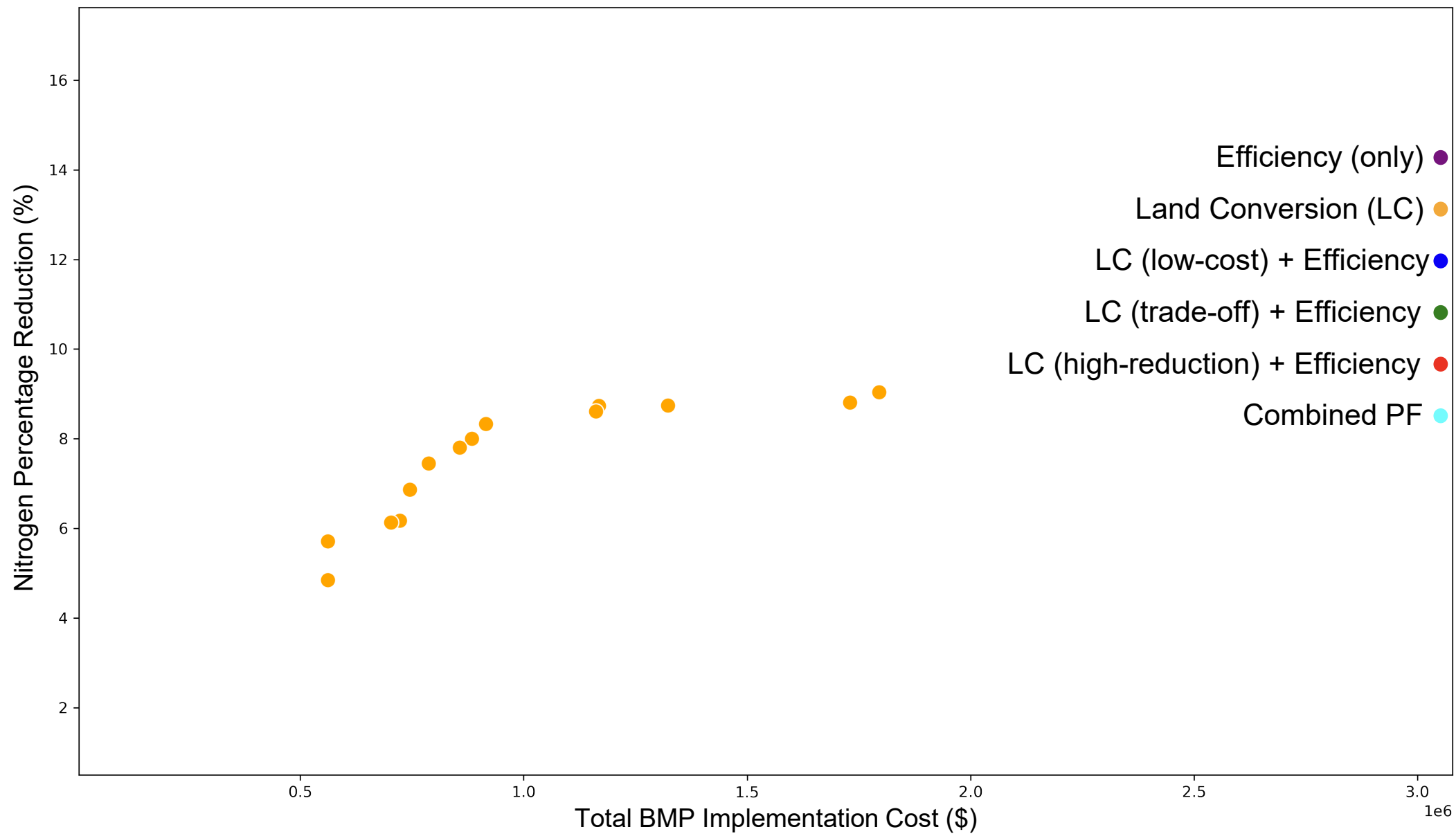
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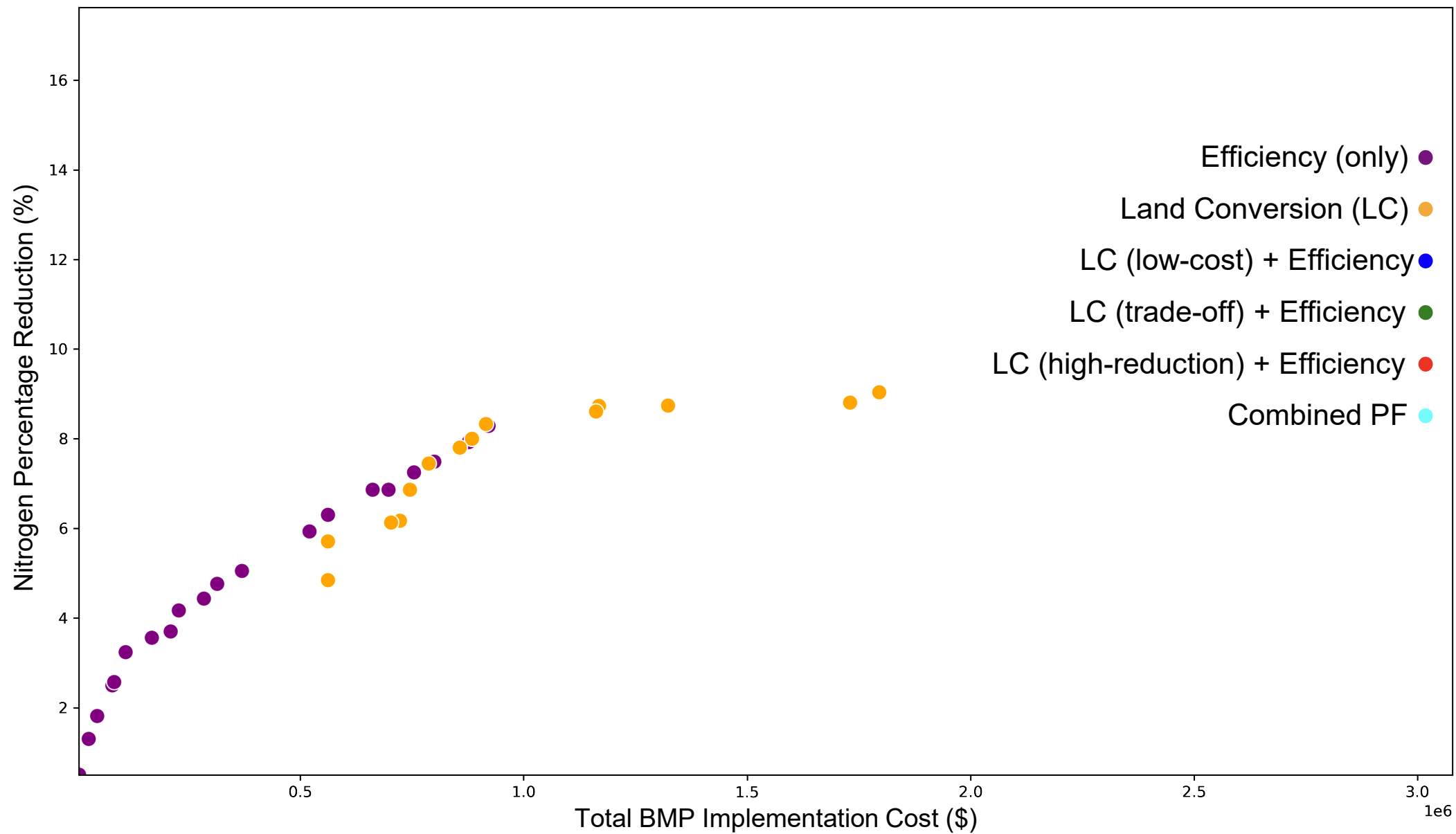
Land Conversion and then Efficiency BMPs (Nelson)

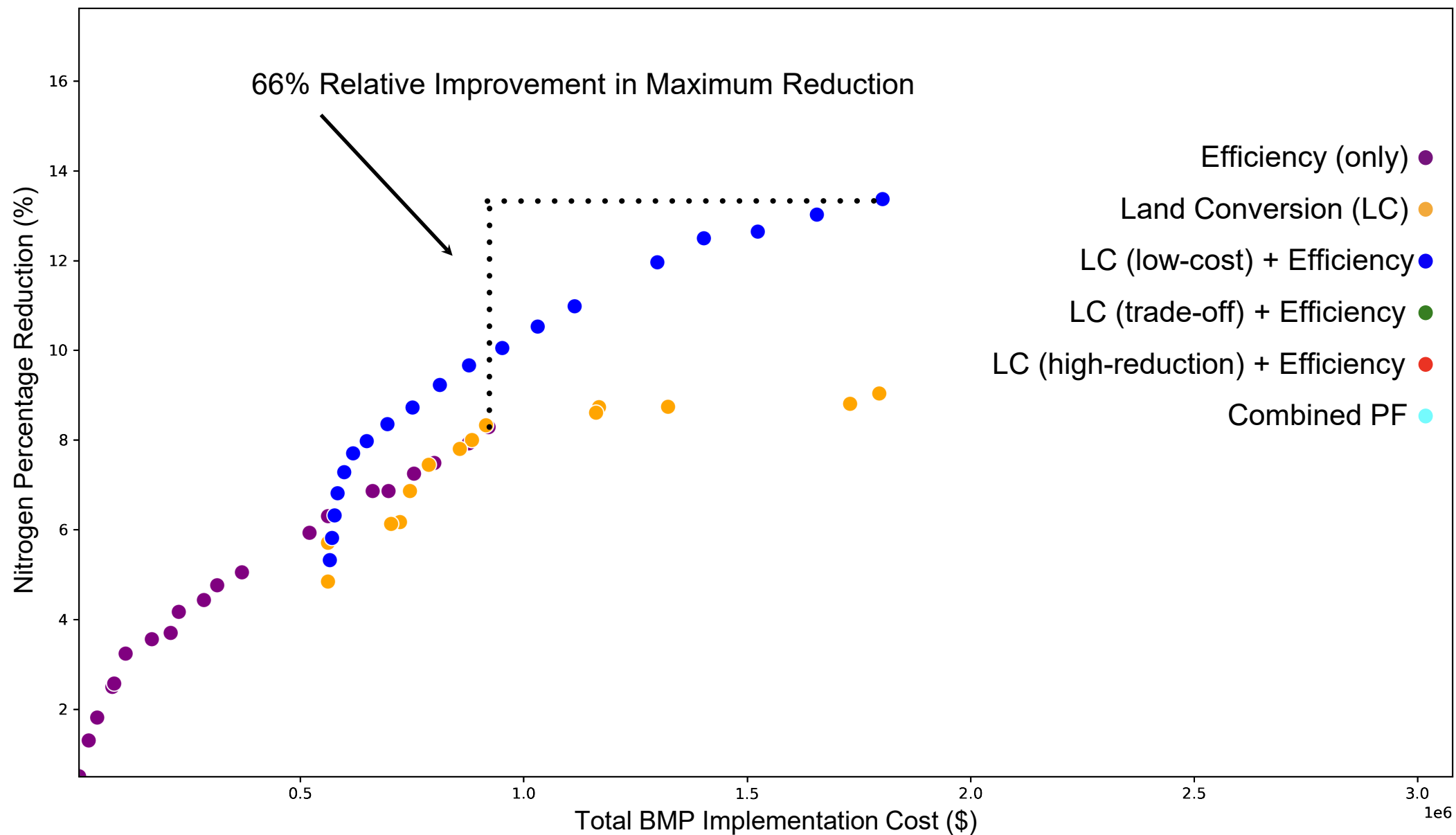


\$500K < Total LC BMP Implantation Cost < \$2M

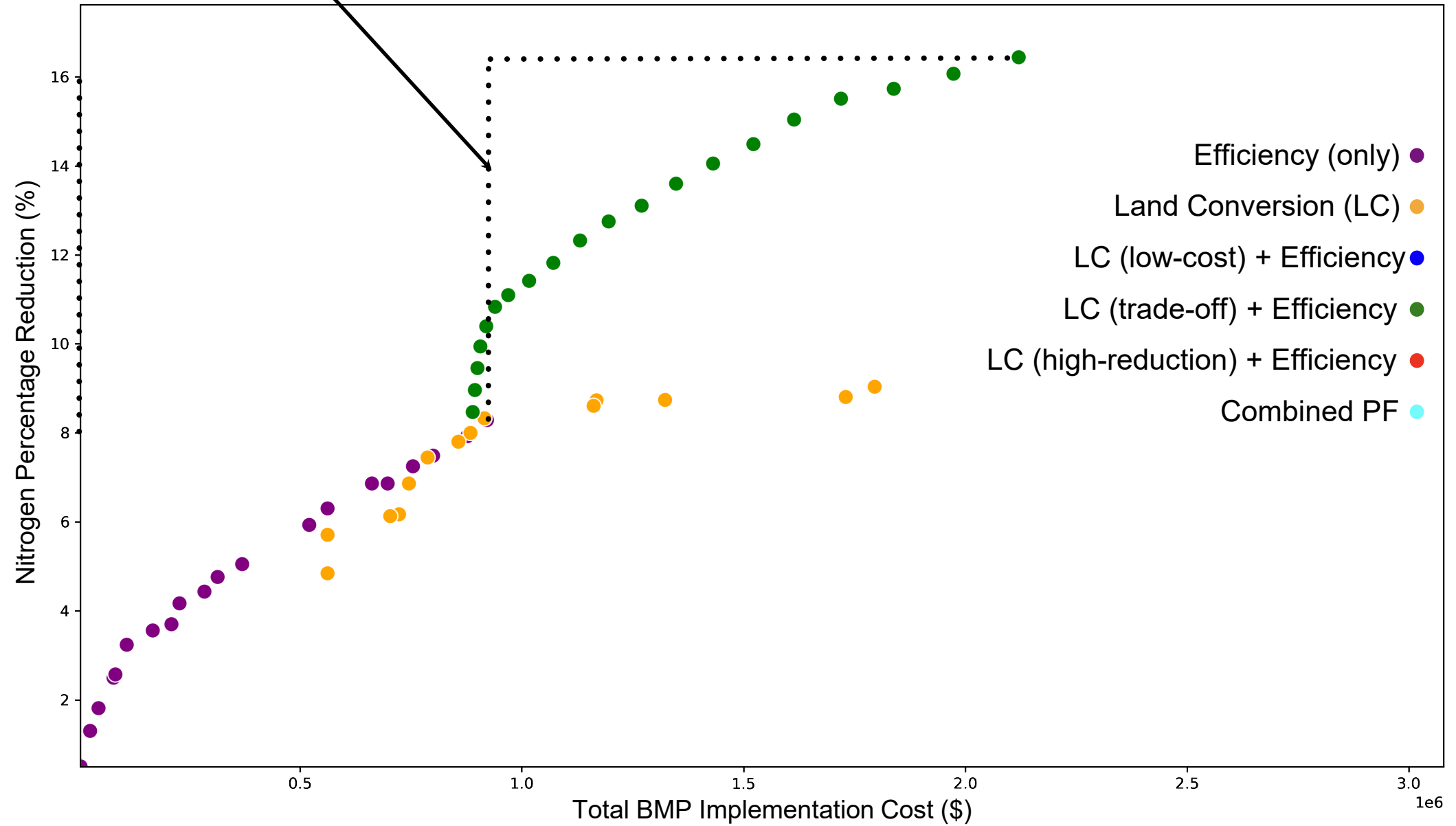


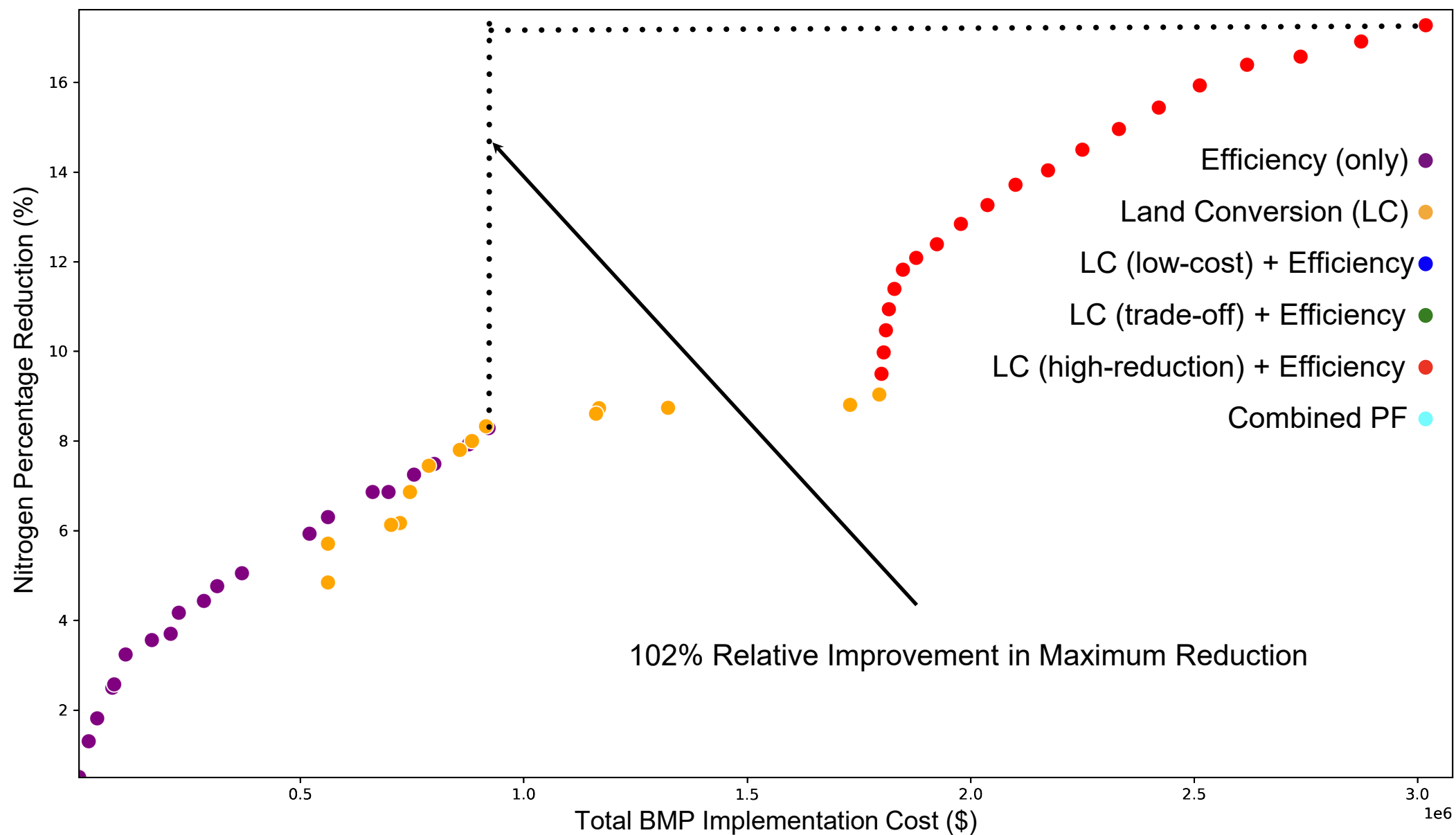


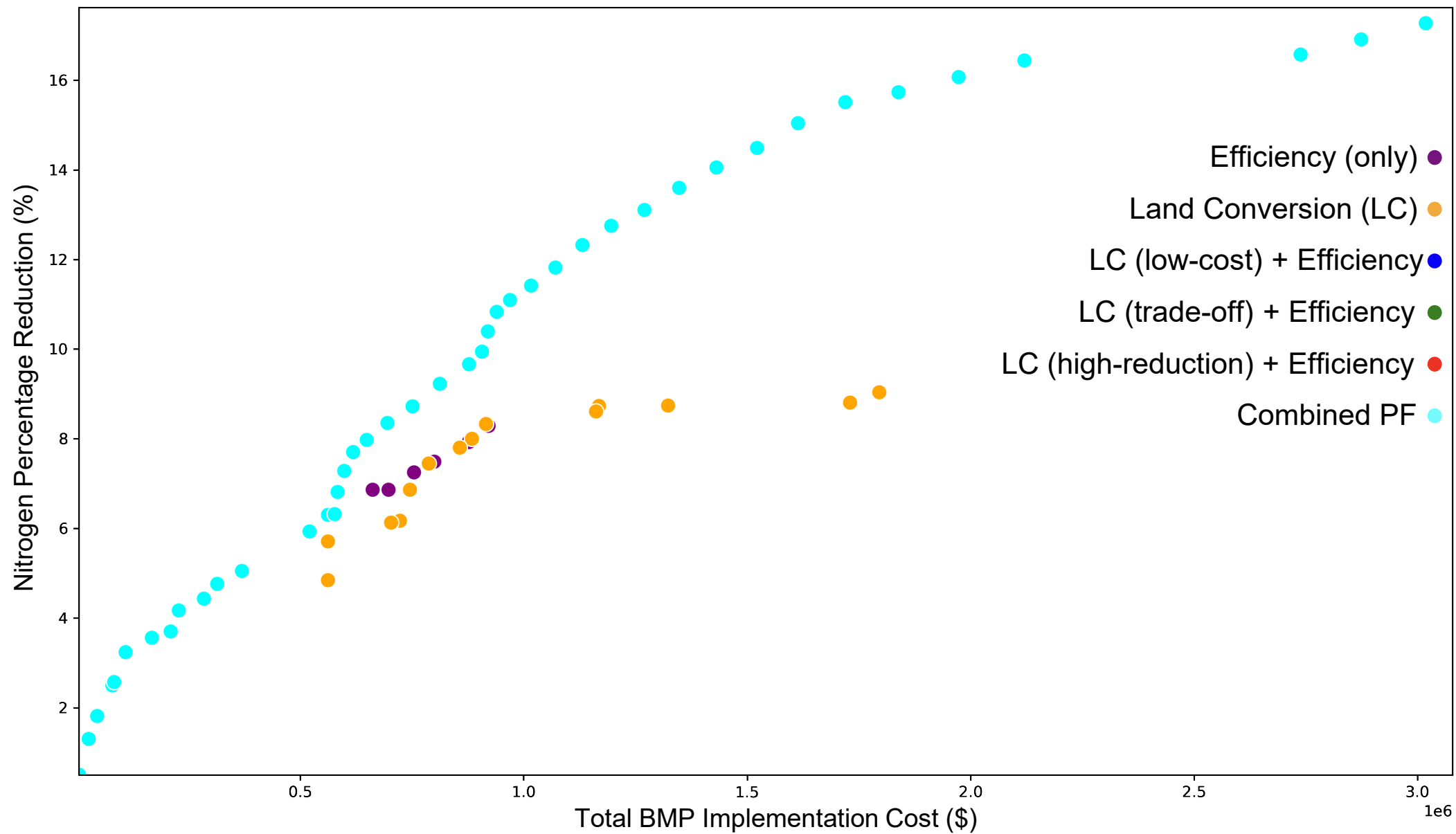




97% Relative Improvement in Maximum Reduction



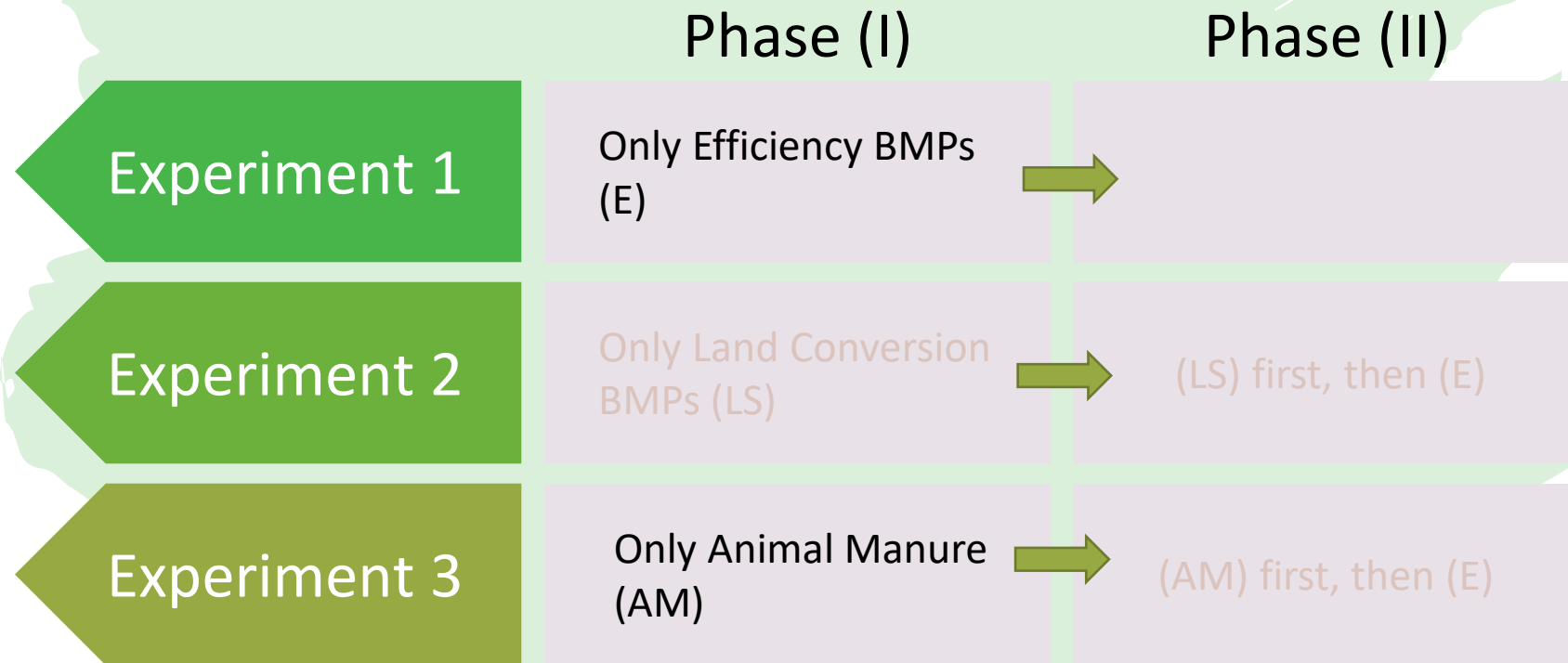


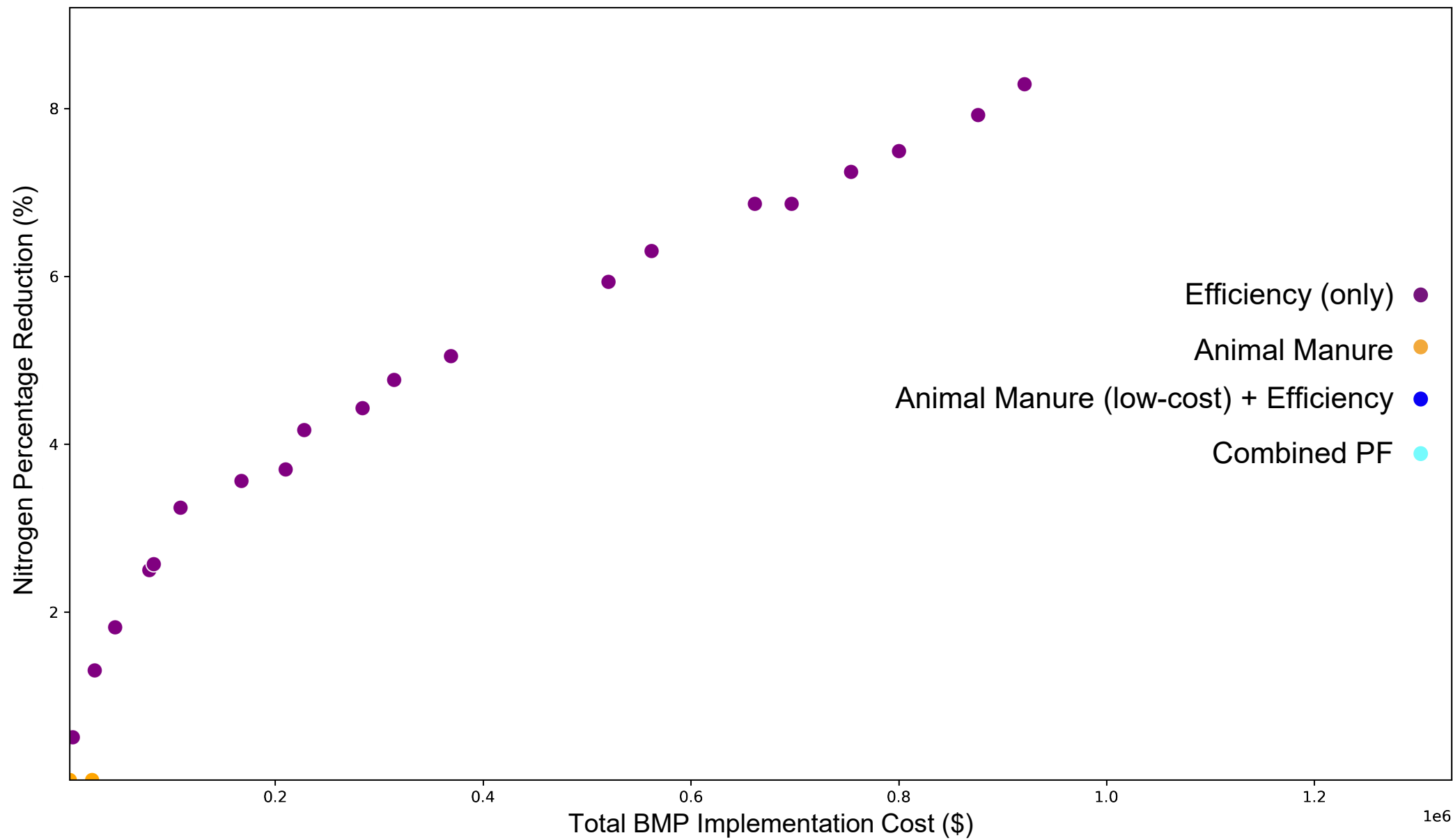




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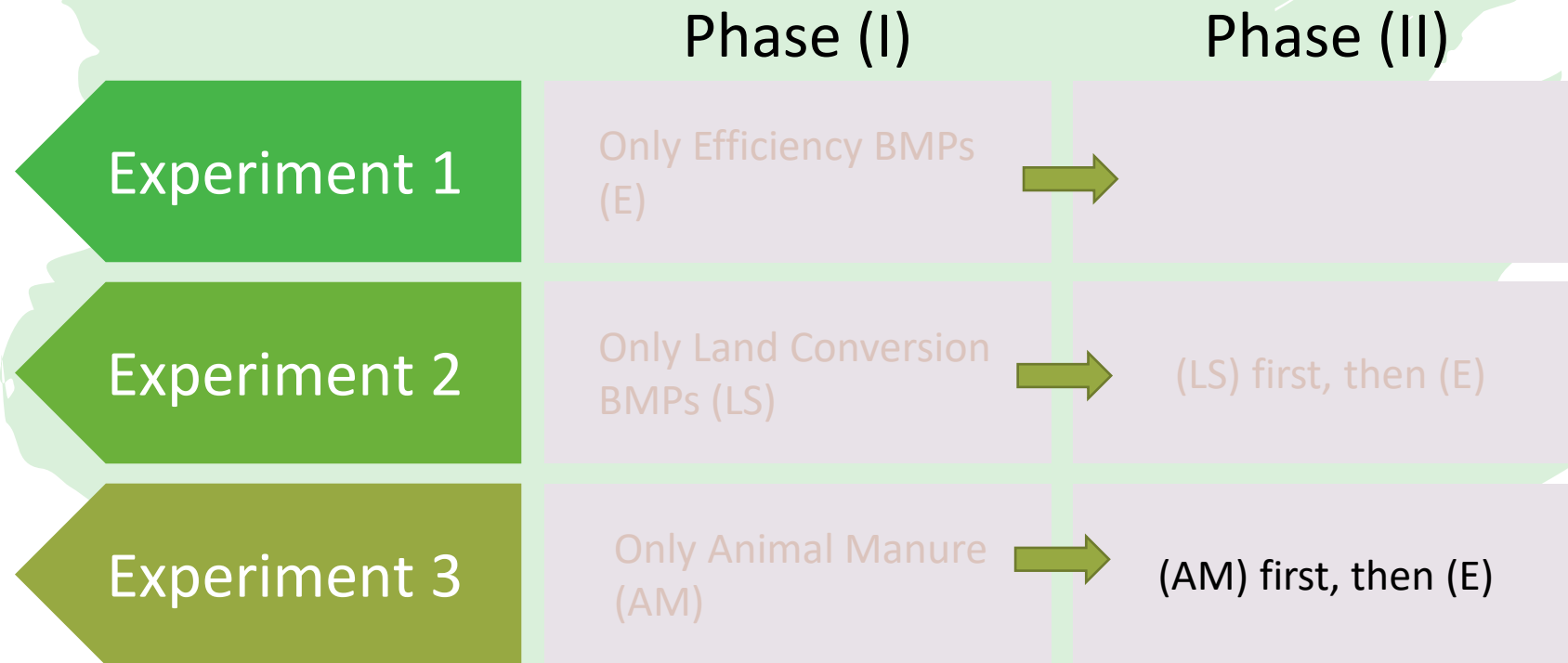
Animal Manure BMPs (Nelson)

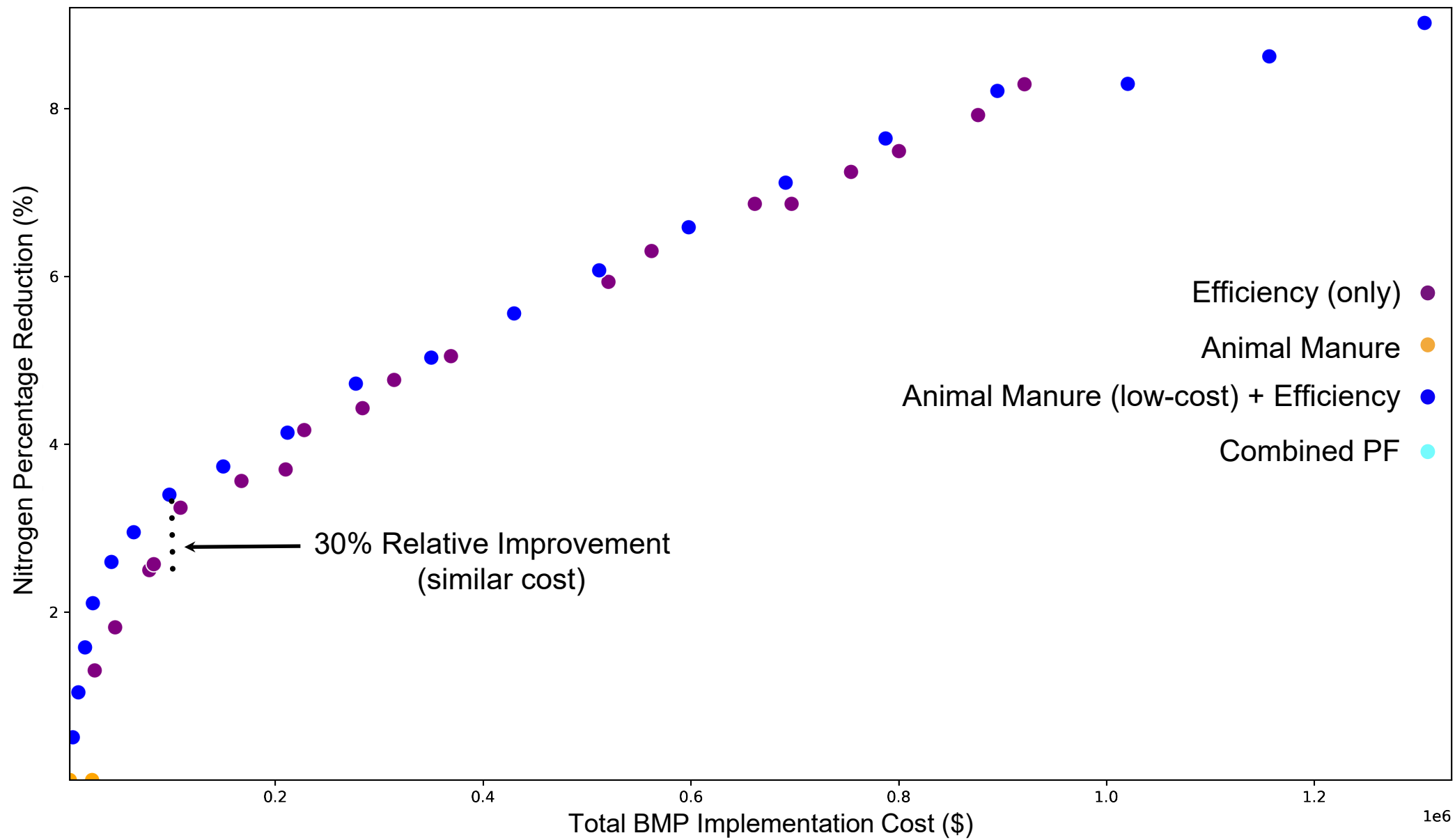


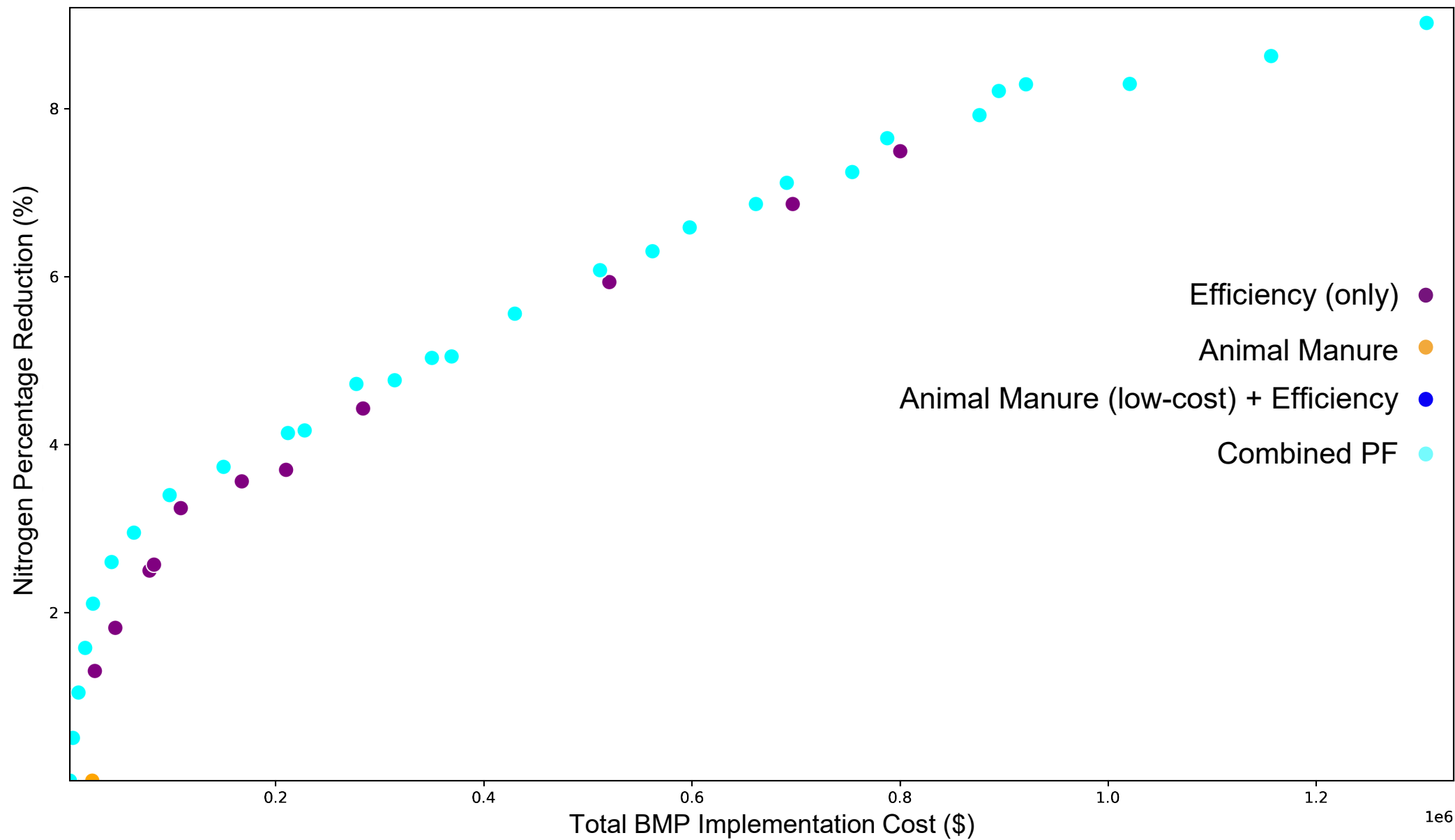


3

Animal Manure and then Efficiency BMPs (Nelson)







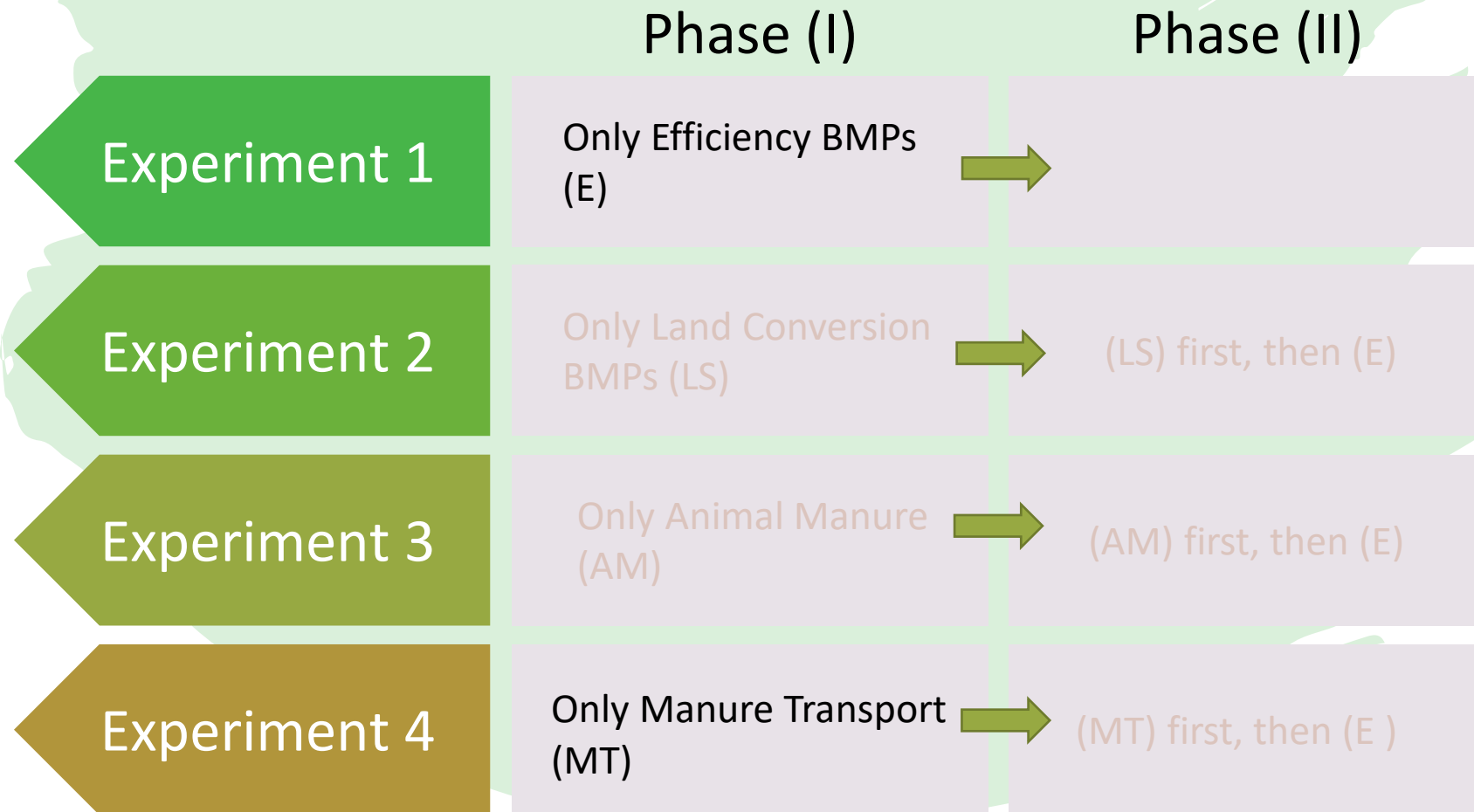
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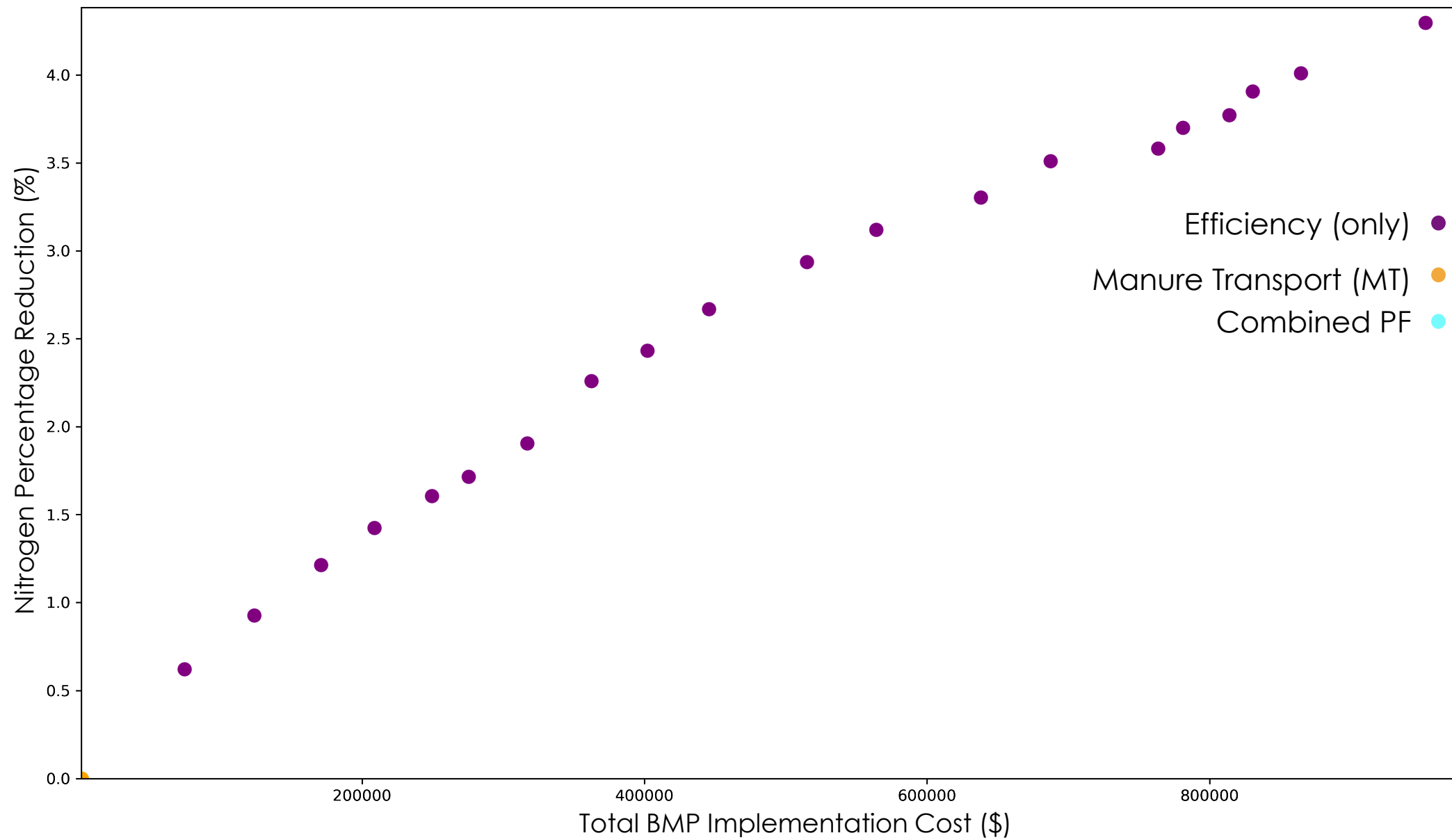
Manure transport BMPs



4

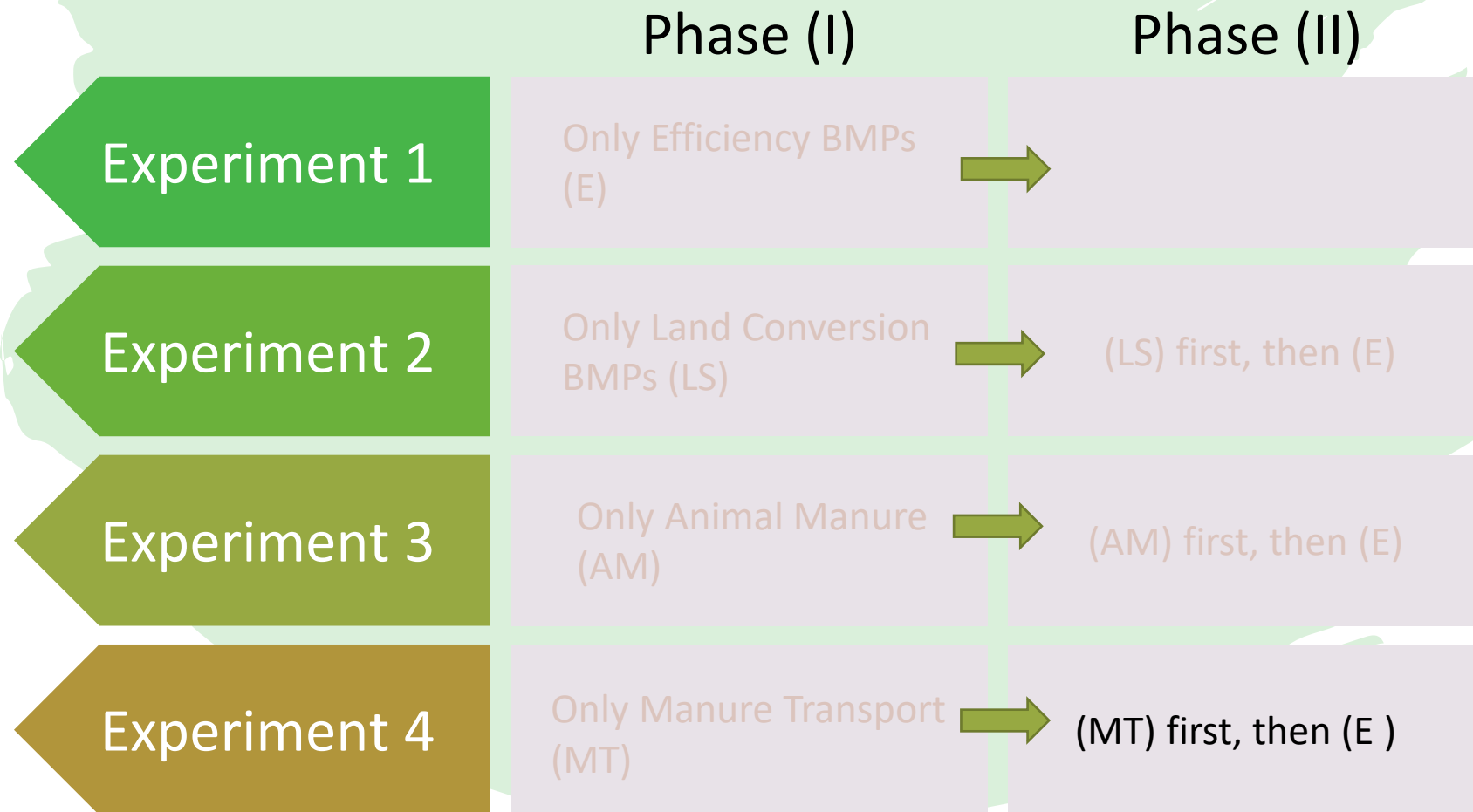
Manure Transport BMPs (Nelson and neighboring countries)

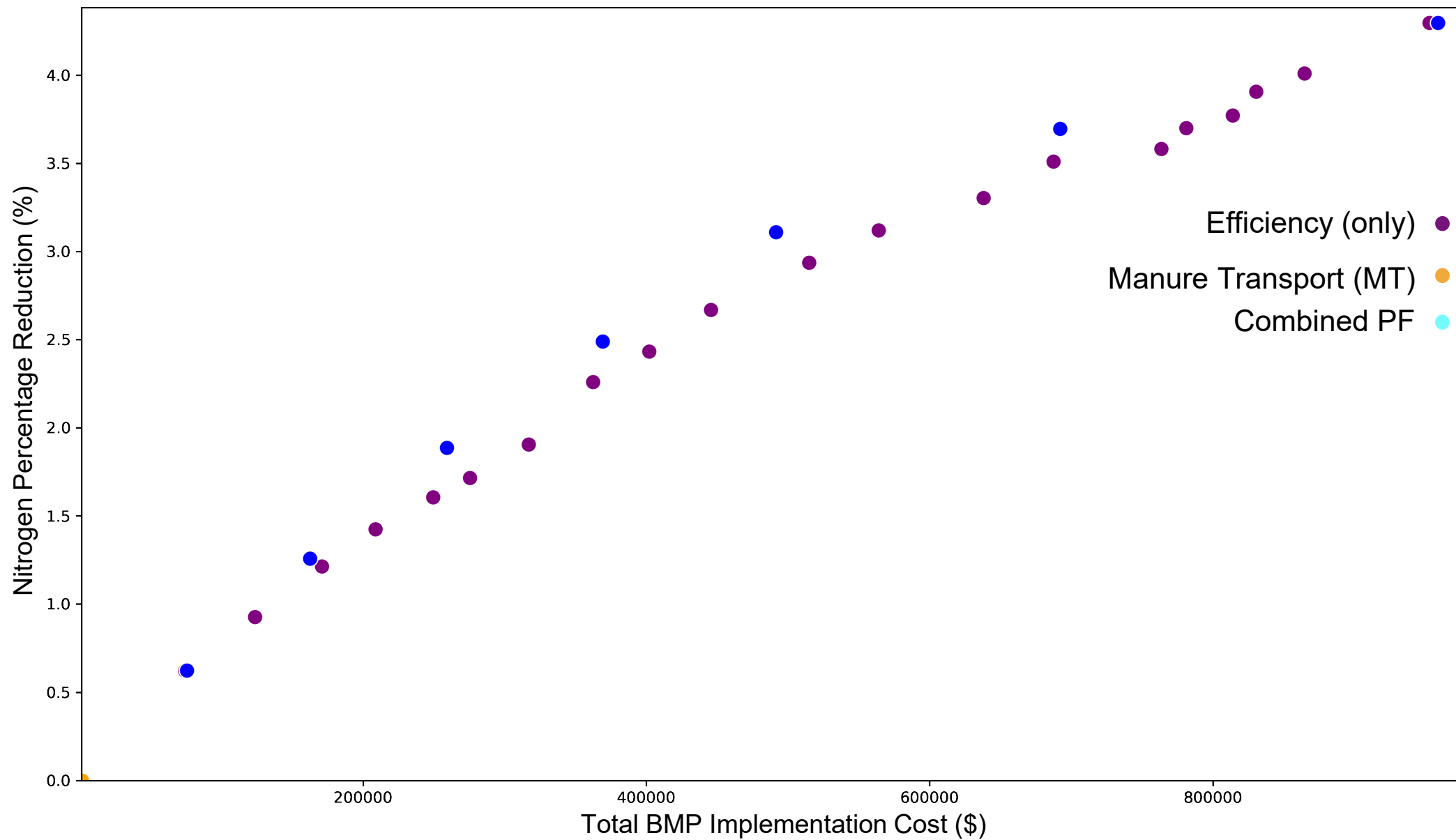


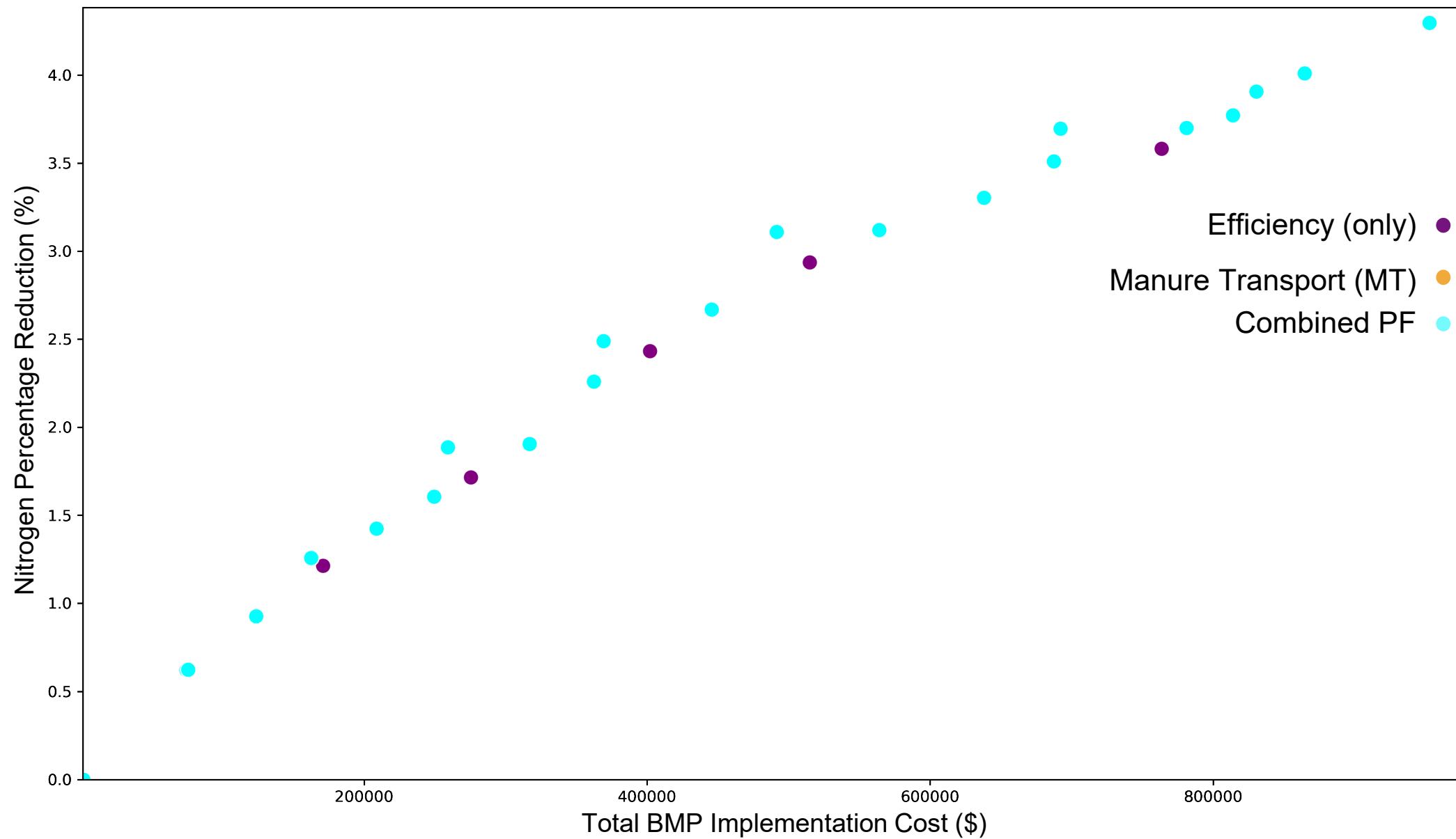


4

Manure Transport BMPs (Nelson and neighboring countries)







Take home message



LC BMPs produce a significant reduction in loads



Animal and manure transport BMPs do not produce good trade-off results



Mixed optimization produced the best results in our studies



Multi-Criteria Decision Making (MCDM)

Multi-Criteria Decision Making

VIKOR

Applications: criteria are conflicting and may have different importance levels

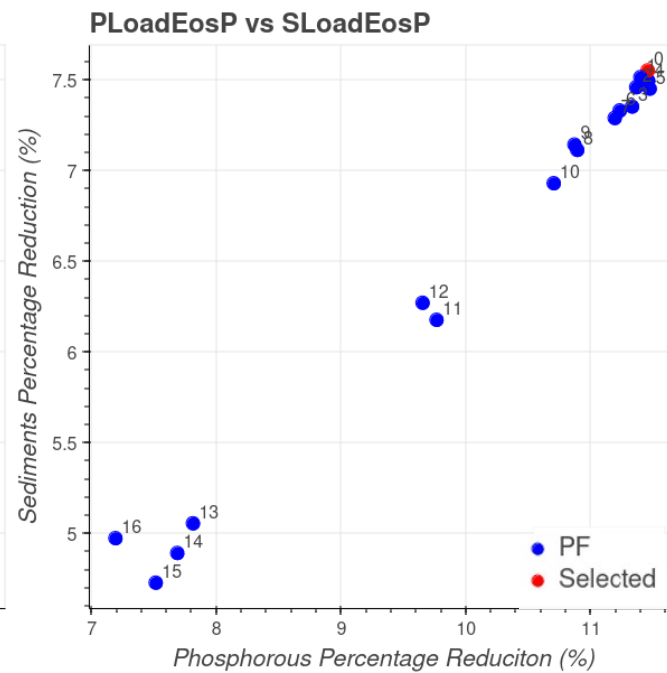
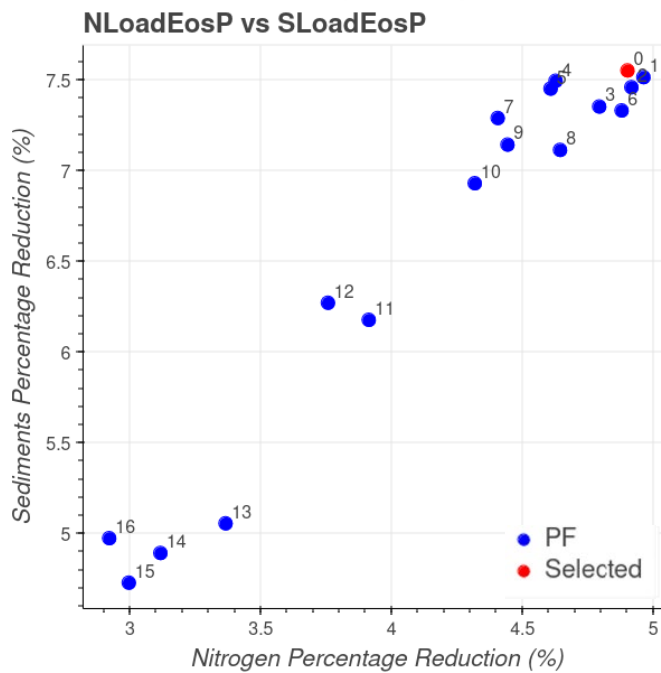
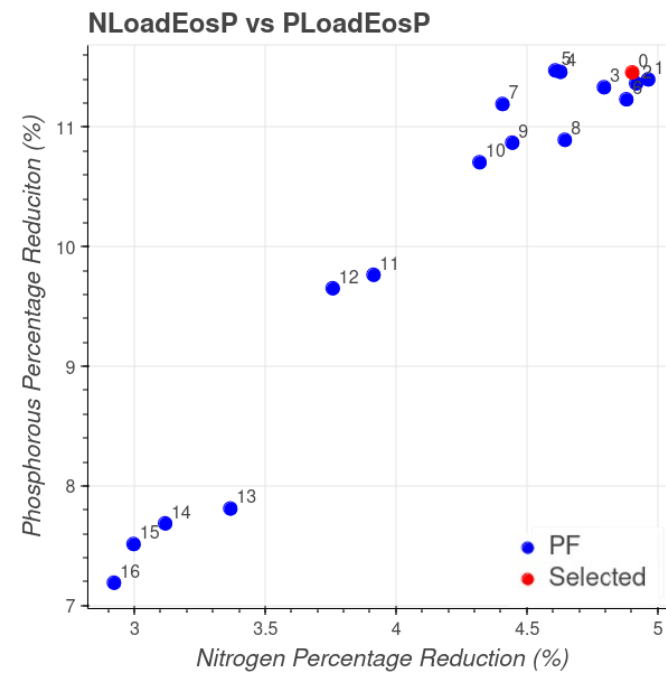
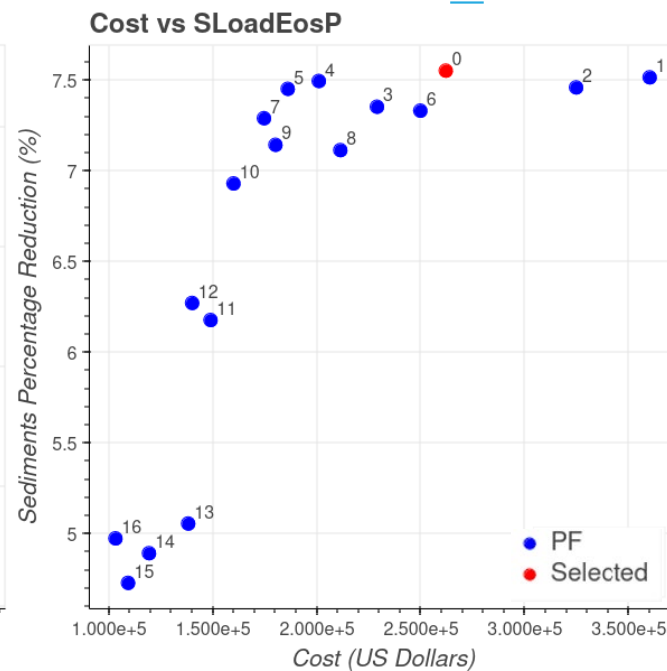
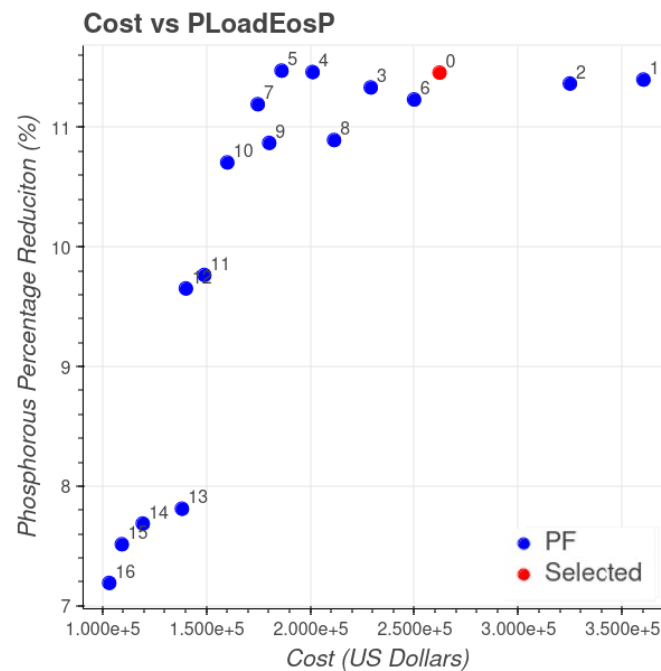
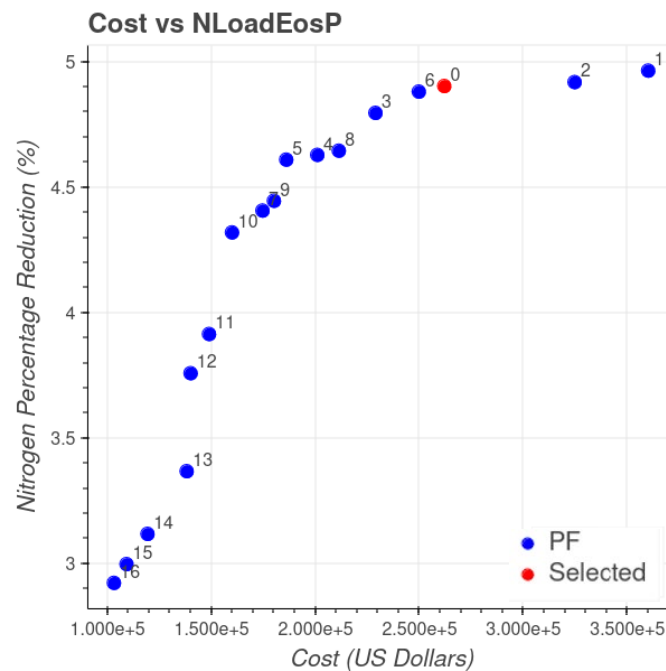
TOPSIS

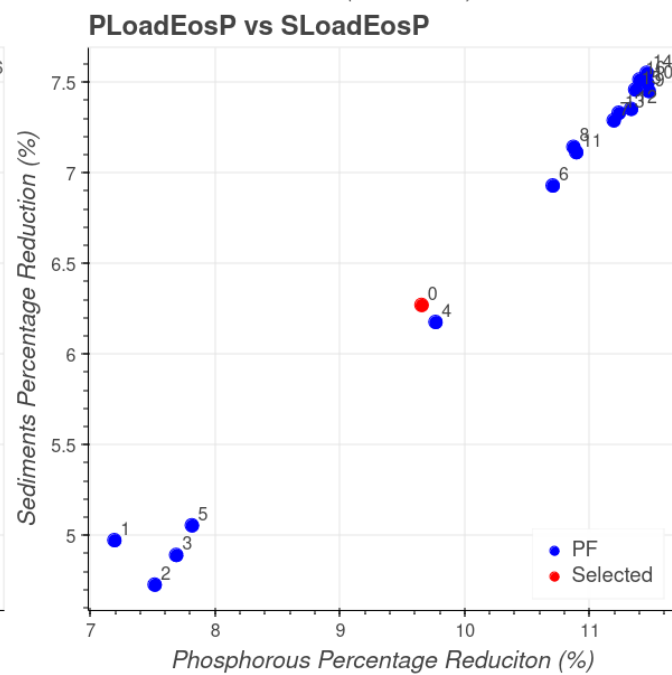
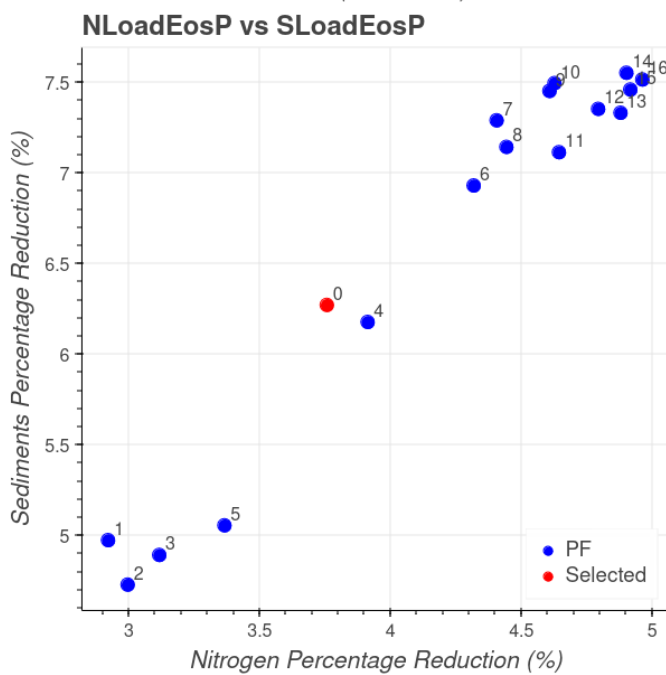
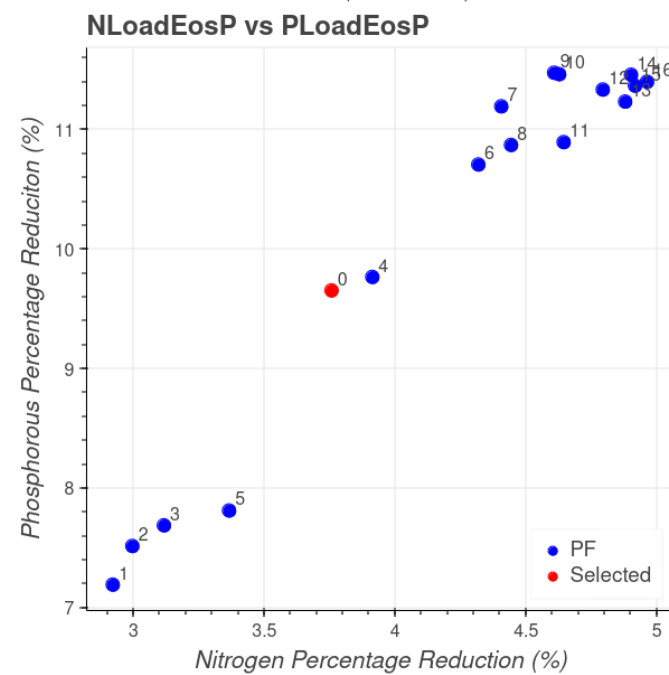
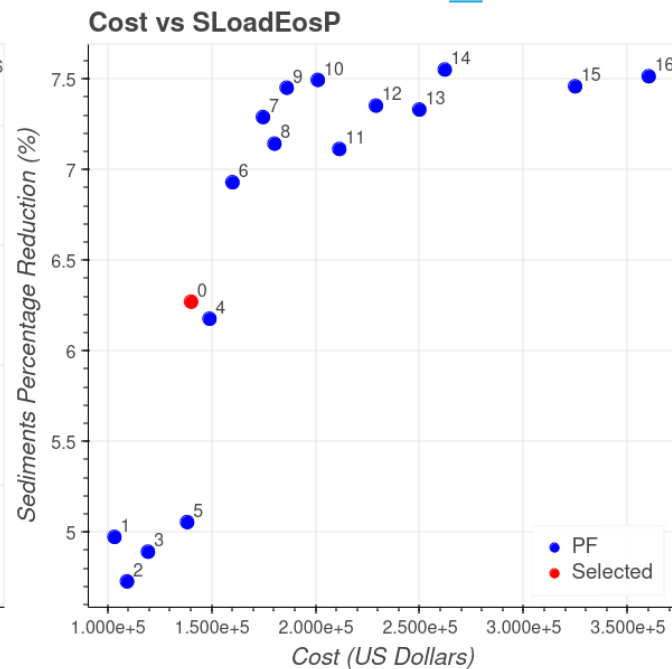
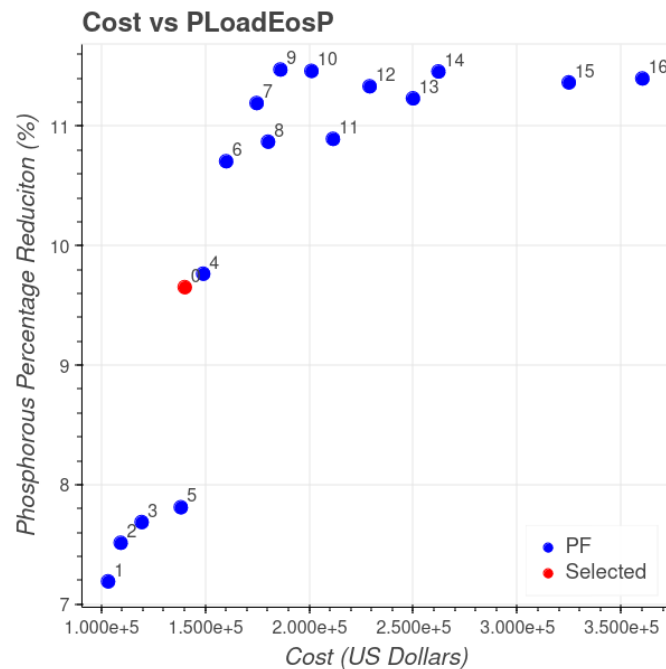
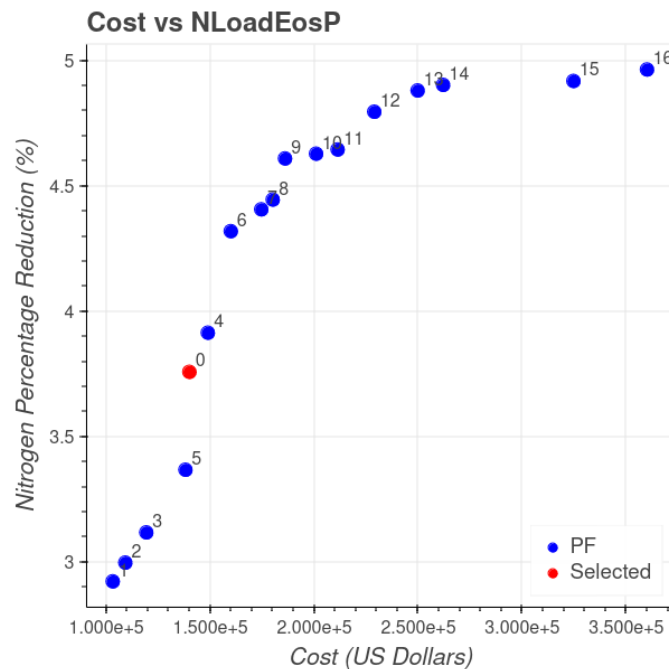
Applications: rank alternatives based on their proximity to the ideal solution



Nelson County

TOPSIS Method

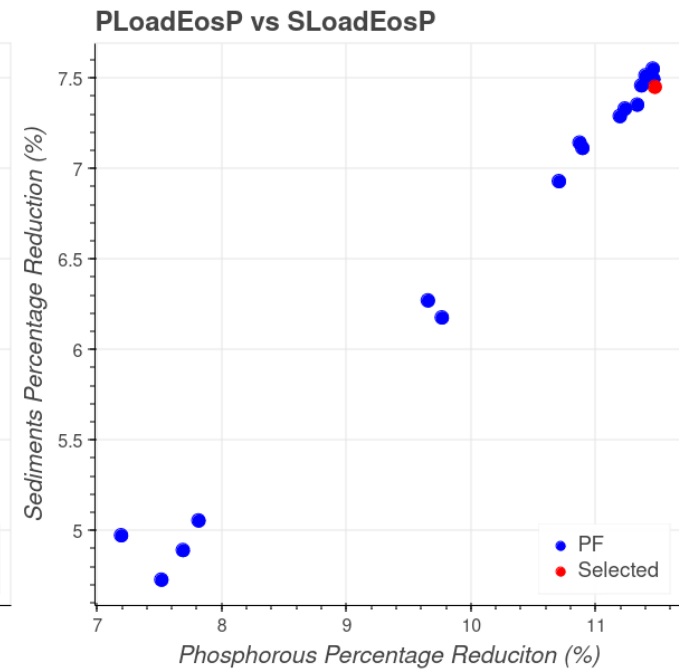


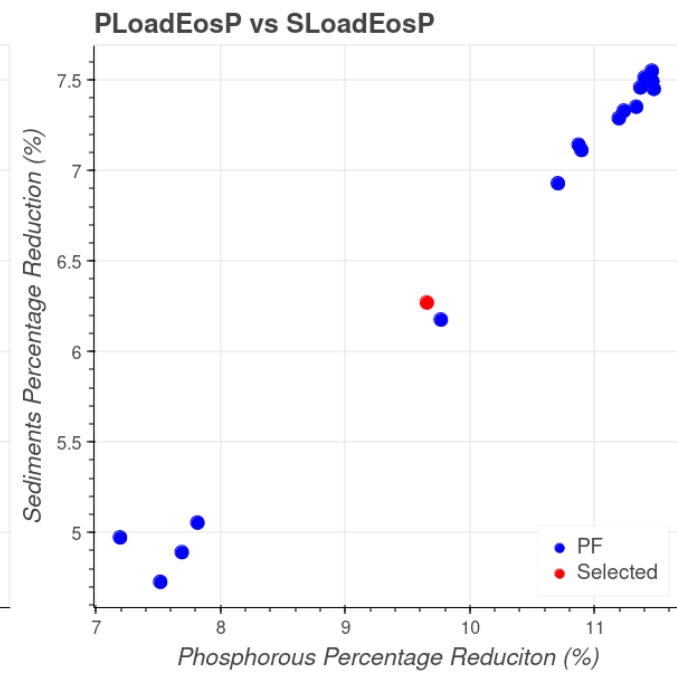




Nelson County

VIKOR Method





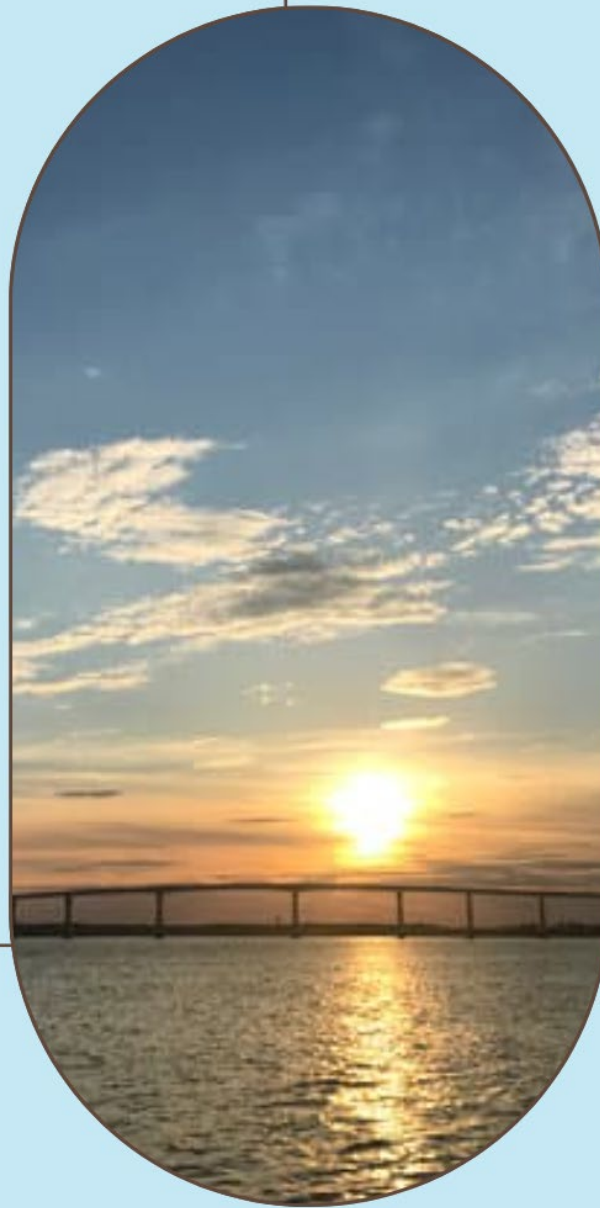
Multi-Criteria Decision Making Tool

NEXT STEP

- Interactive Optimization-Decision making
- Extensions to more counties and states
- Validation of our results on some critical county/state cases
- Parallel computing platform for faster execution
- Uncertainty and other practicality handling
- Workshops with CBP users for feedback and improvement of our approaches

Chesapeake Bay Optimization Webinars

Join experts in the discussion
of bay preservation.



2024 Chesapeake Bay Optimization Webinars



Objective:

- * Raise awareness about our BMP optimization framework.
- * Train users and practitioners to use the framework to optimize real-world scenarios.



Features:

- * Interactive show of the framework capabilities
- * Interactive Q&A sessions



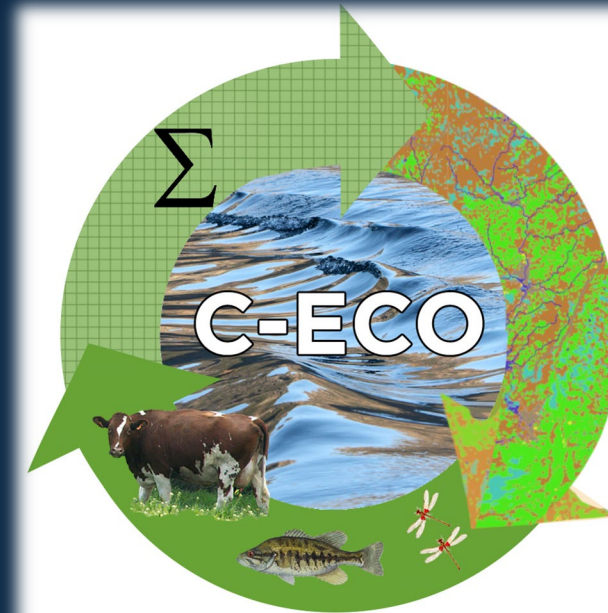
Benefits:

- * Enhanced decision-making
- * Foster community collaborations
- * Efficient BMP implementations
- * Feedback



Computational Optimization and Innovation

Thank you



Computational Ecohydrology