Modeling Workgroup Meeting Quarterly Review

January 2024

Optimization Update

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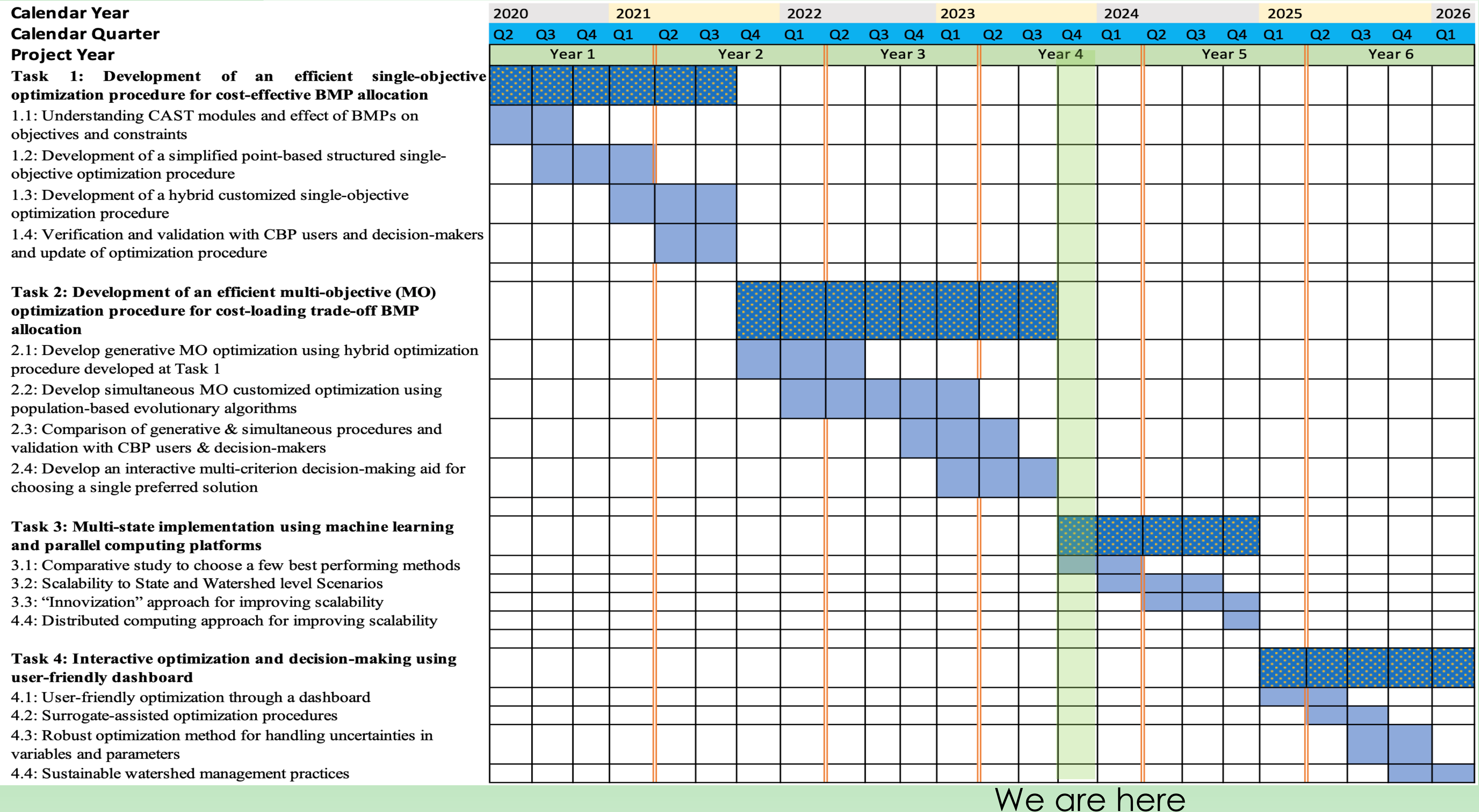
AGENDA

1	Timeline
2	Overview
3	From West Virginia to Chesapeake Bay
4	Goals and Objectives
5	Interactive Optimization and Decision-Making
6	Next steps
7	2024 Chesapeake Bay Optimization Webinars

Timeline of the Project



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

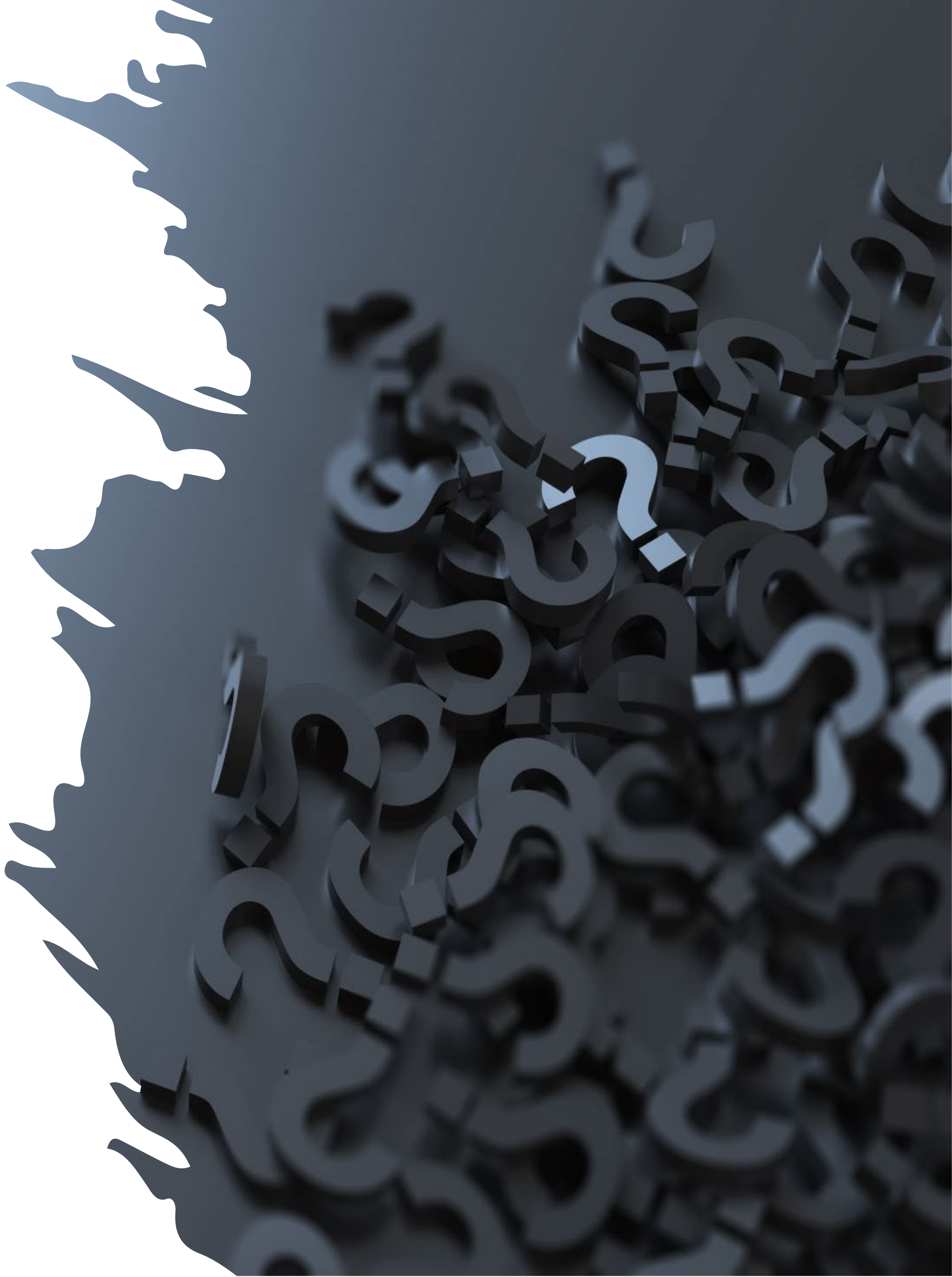
3.4 Distributed computing approach for improving scalability

Timeline of the Project


OVERViEW

Problem Statement

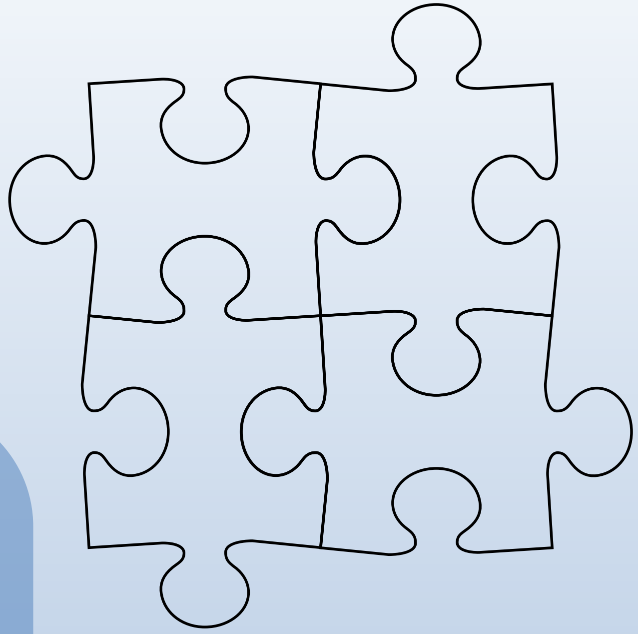
One of the most challenging issues for a real-world optimization problem is the ***Search Space Complexity*** (variables and constraints), especially for the CBW management problem.



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.



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

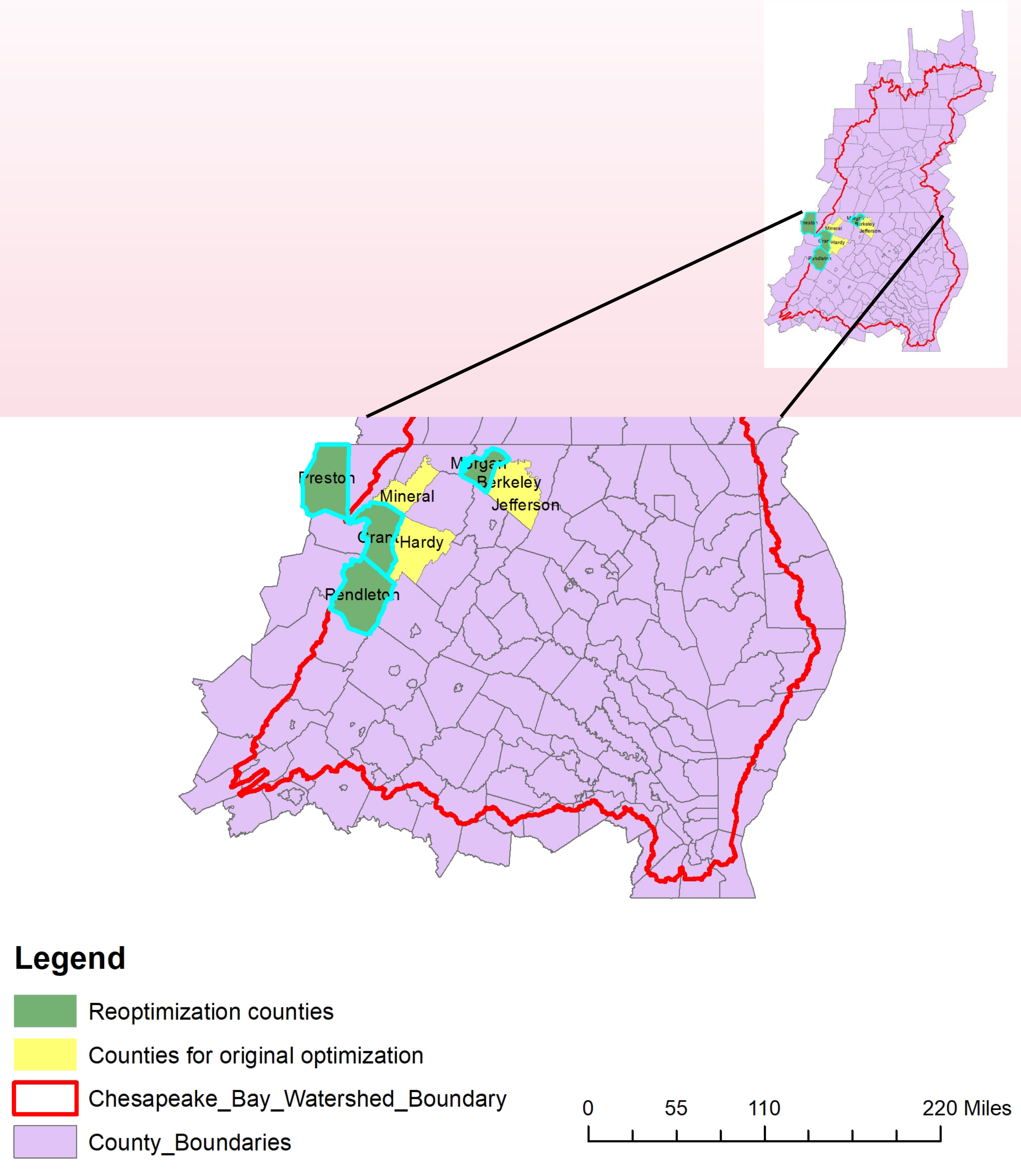
The number of variables and constraints depends on **the scale of the county or state** under study.

West Virginia

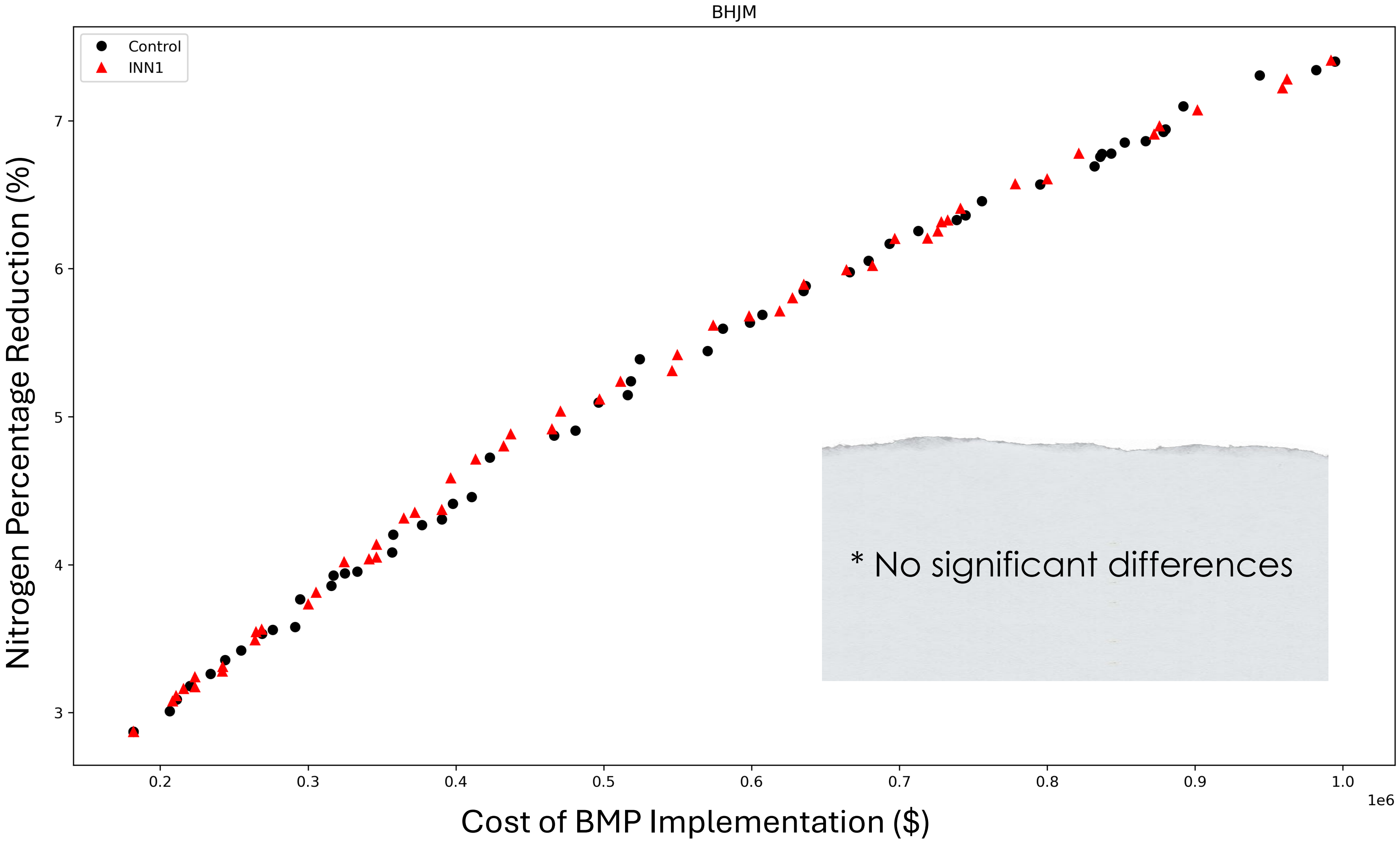
Four county: 65,260 variables (Berkeley, Jefferson, Mineral, and Hardy)

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

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



Compare Original vs. Innovized Optimization
Berkeley, Hardy, Jefferson, and Mineral Counties



Re-optimization-Validation

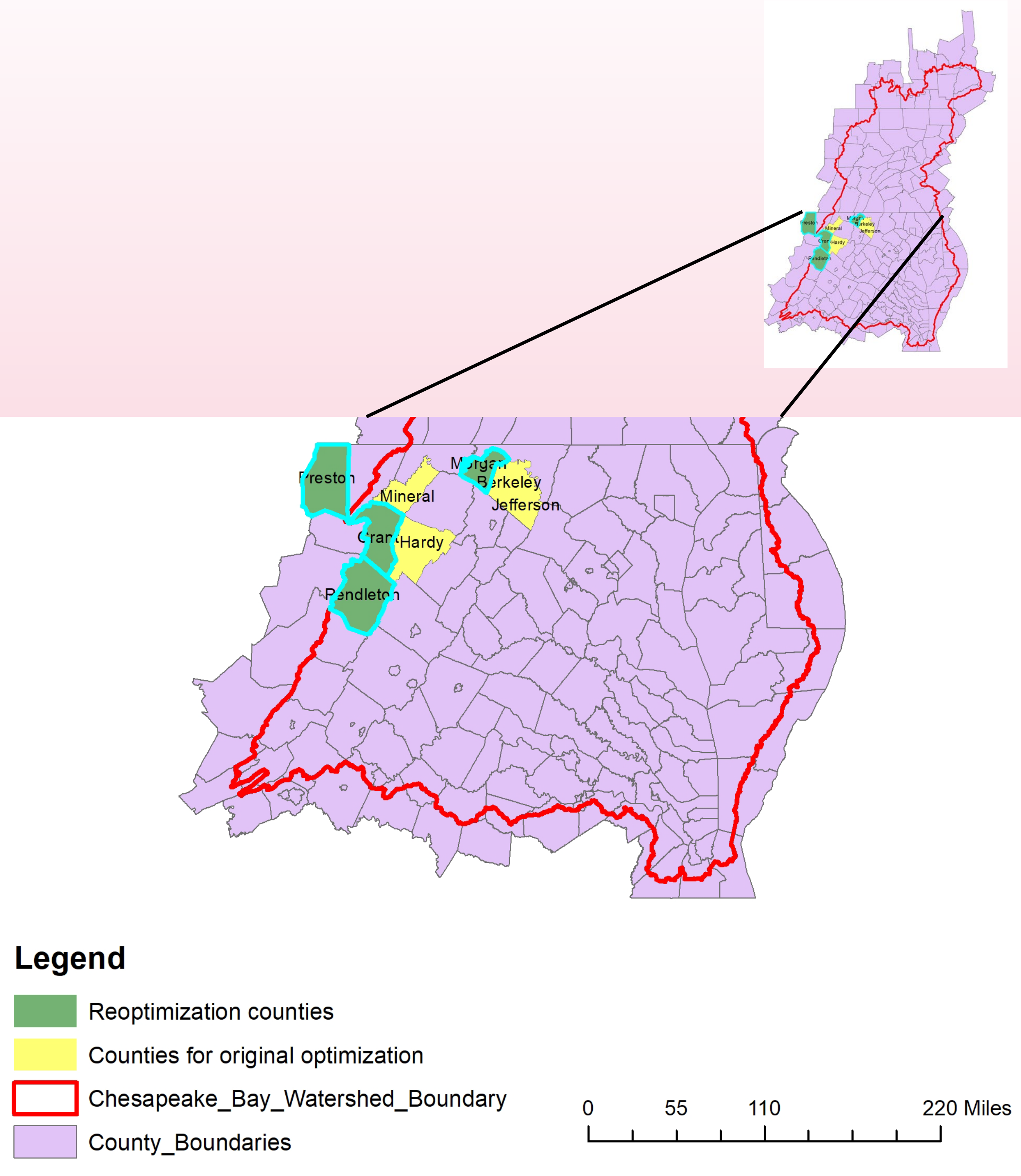
Reoptimization

Evaluate the performance of original innovization technique other counties

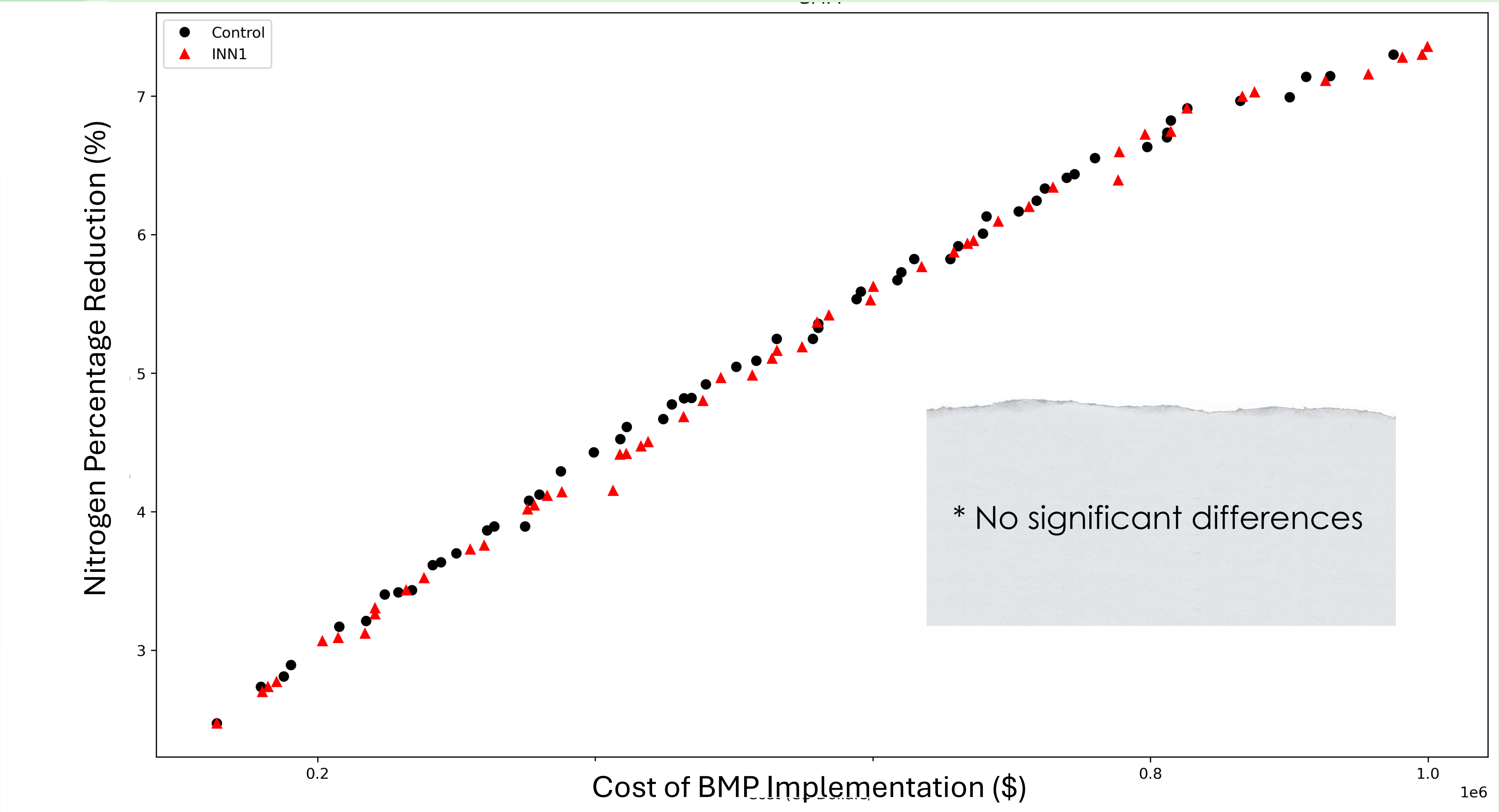
West Virginia

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

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



Reoptimization
Compare Original vs. Innovized Optimization
Grant, Morgan, Pendleton, and Preston 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.

“From West Virginia to Chesapeake Bay

Challenge

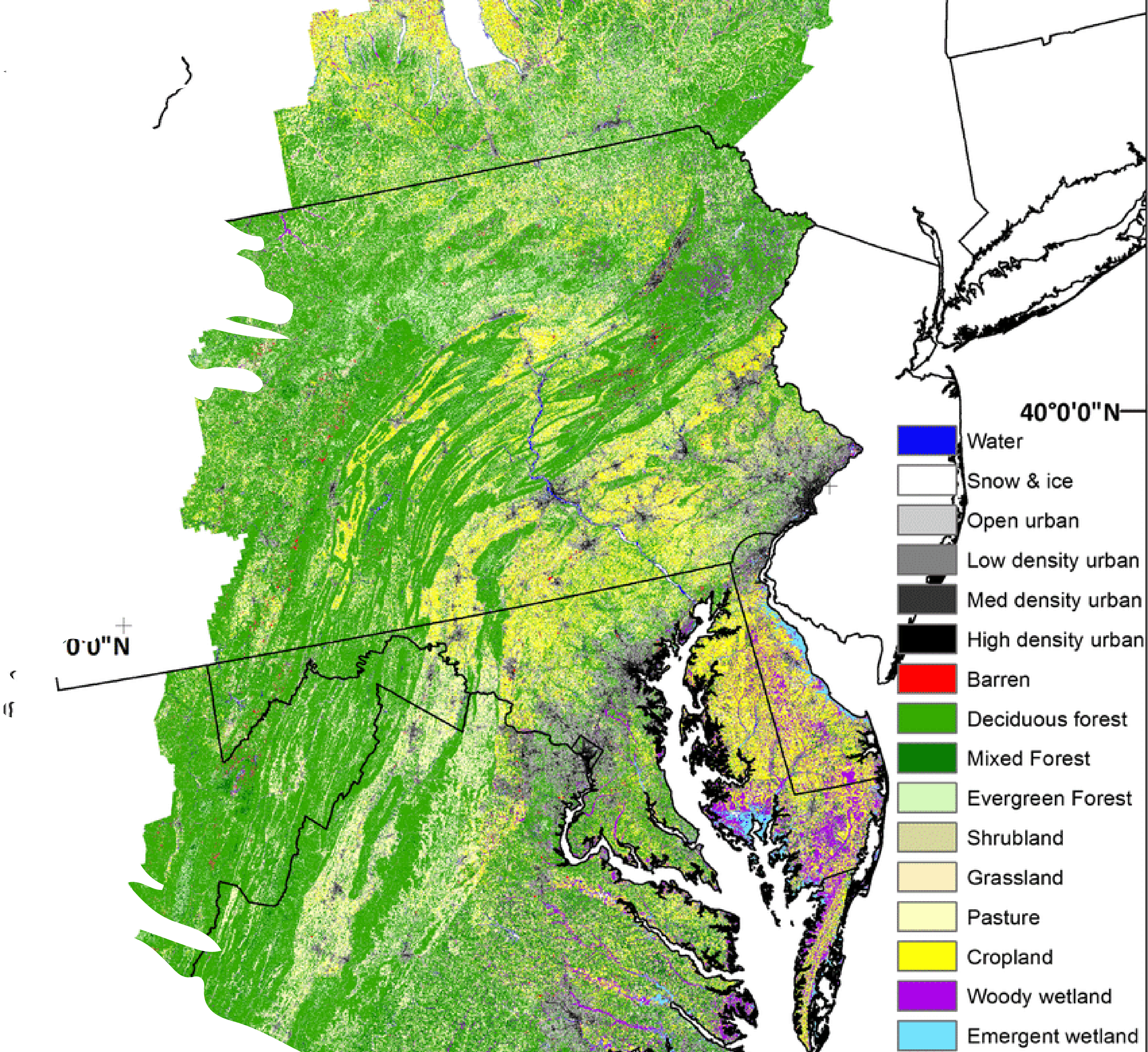
Innovization methods in WV effectively:

- **reduce optimization problem size**
- **lower computational time and resources**

Study Area

Challenge

Innovization methods in WV **don't fully represent the diverse load sources and land use traits of the entire Chesapeake Bay watershed**.



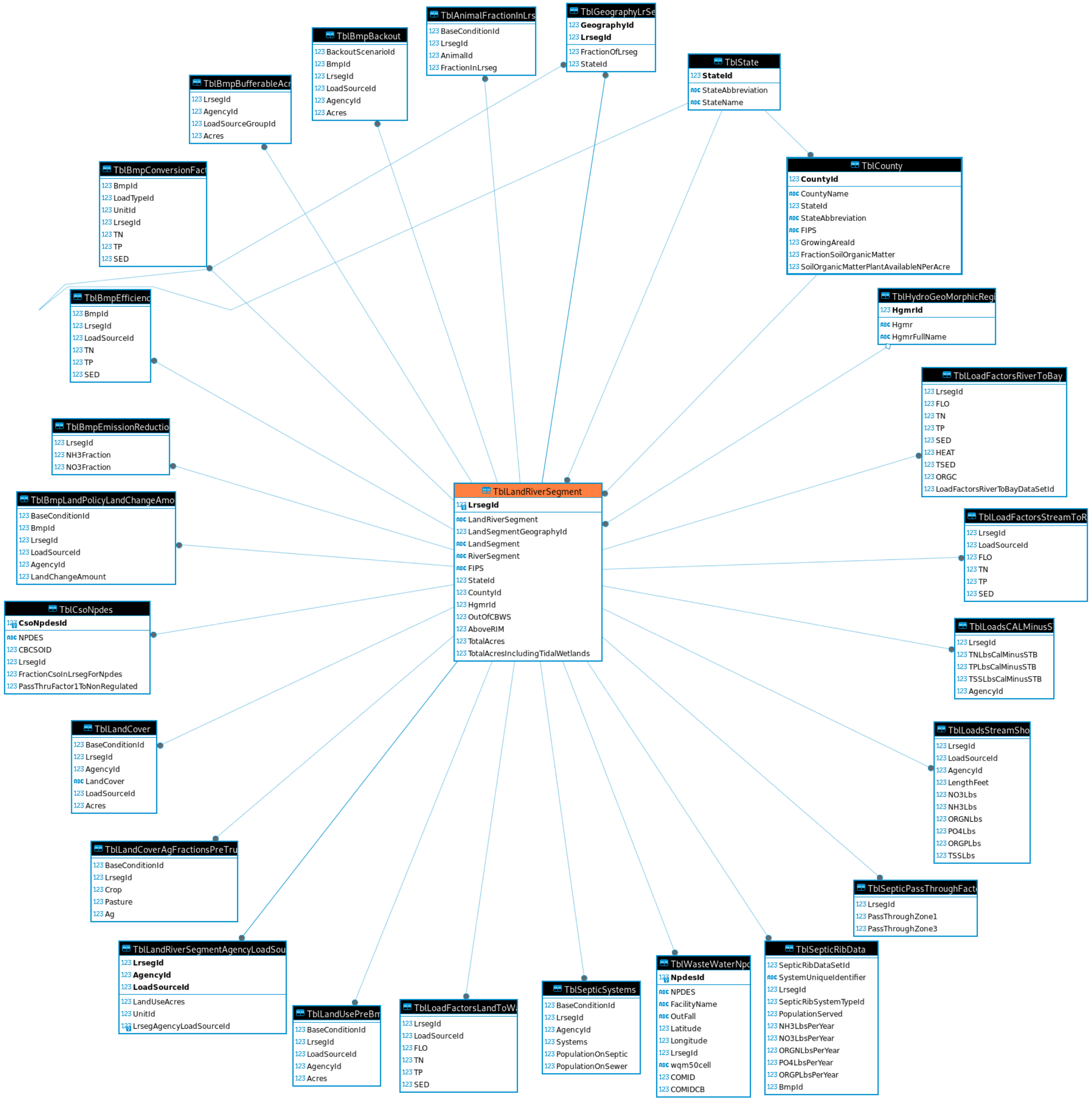
Goal

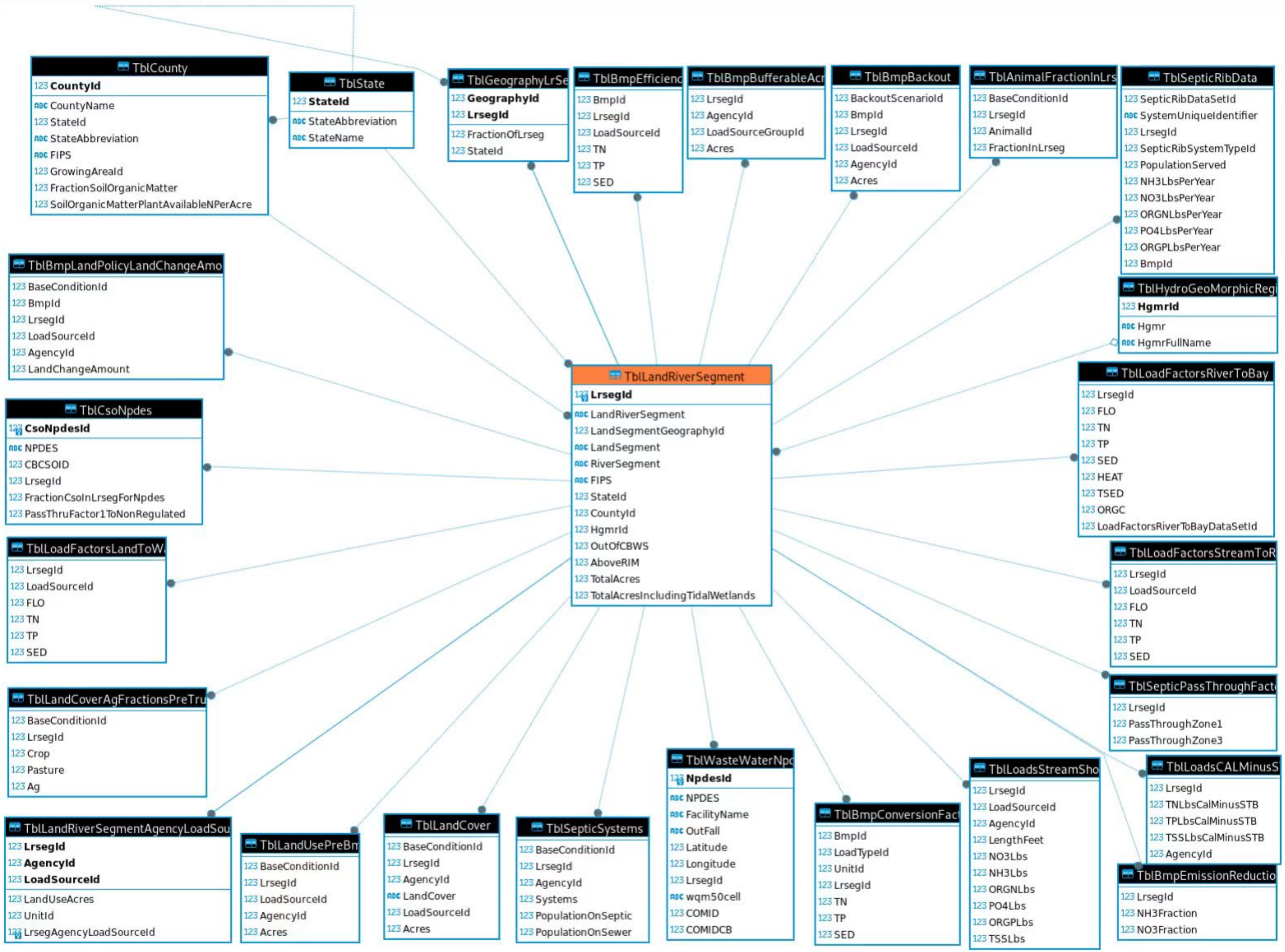
- Our goal is to develop a more comprehensive approach that encompasses the entirety of the Chesapeake Bay watershed.

Objectives

Identify	Identify the most relevant variables.
Recognize	Recognize areas with similarities concerning the watershed features established in the first objective.
Determine	Determine the most frequently chosen BMPs for various land river segments.
Offer	Offer recommendations on selecting the most appropriate BMPs for optimization through the application of artificial intelligence methods.
Examine	Examine the reliability of the proposed strategy within the Chesapeake Bay Watershed.

Step 1: Variable Selection





TblCounty
CountyId
CountyName
StateId
StateAbbreviation
FIPS
GrowingAreaId
FractionSoilOrganicMatter
SoilOrganicMatterPlantAvailableNPerAcre
TblState
StateId
StateAbbreviation
StateName
TblGeographyLrSe
GeographyId
LrsegId
FractionOfLrseg
StateId
TblBmpEfficienc
BmpId
LrsegId
LoadSourceId
TN
TP
SED
TblBmpBufferableAcr
LrsegId
AgencyId
LoadSourceGroupId
Acres
TblBmpBackout
BackoutScenarioId
BmpId
LrsegId
LoadSourceId
AgencyId
Acres
TblAnimalFractionInLrs
BaseConditionId
LrsegId
AnimalId
FractionInLrseg
TblSepticRibData
SepticRibDataSetId
SystemUniqueIdentifier
LrsegId
SepticRibSystemTypeId
PopulationServed
NH3LbsPerYear
NO3LbsPerYear
ORGNLbsPerYear
PO4LbsPerYear
ORGPLbsPerYear
BmpId
TblHydroGeoMorphicRegi
HgmrId
Hgmr
HgmrFullName
TblBmpLandPolicyLandChangeAmo
BaseConditionId
BmpId
LrsegId
LoadSourceId
AgencyId
LandChangeAmount
TblLandRiverSegment
LrsegId
LandRiverSegment
LandSegmentGeographyId
LandSegment
RiverSegment
FIPS
StateId
CountyId
HgmrId
OutOfCBWS
AboveRIM
TotalAcres
TotalAcresIncludingTidalWetlands
TblLoadFactorsRiverToBay
LrsegId
FLO
TN
TP
SED
HEAT
TSED
ORGC
LoadFactorsRiverToBayDataSetId
TblCsoNpdes
CsoNpdesId
NPDES
CBCSOID
LrsegId
FractionCsoInLrsegForNpdes
PassThruFactor1ToNonRegulated
TblLoadFactorsLandToW
LrsegId
LoadSourceId
FLO
TN
TP
SED
TblLoadFactorsStreamToR
LrsegId
LoadSourceId
FLO
TN
TP
SED
TblLandCoverAgFractionsPreTru
BaseConditionId
LrsegId
Crop
Pasture
Ag
TblSepticPassThroughFact
LrsegId
PassThroughZone1
PassThroughZone3
TblLoadsCALMinusS
LrsegId
TNLbsCalMinusSTB
TPLbsCalMinusSTB
TSSLbsCalMinusSTB
AgencyId
TblLandRiverSegmentAgencyLoadSou
LrsegId
AgencyId
LoadSourceId
LandUseAcres
UnitId
LrsegAgencyLoadSourceId
TblLandUsePreBm
BaseConditionId
LrsegId
LoadSourceId
AgencyId
Acres
TblLandCover
BaseConditionId
LrsegId
AgencyId
LandCover
LoadSourceId
Acres
TblSepticSystems
BaseConditionId
LrsegId
AgencyId
Systems
PopulationOnSeptic
PopulationOnSewer
TblWasteWaterNpd
NpdesId
NPDES
FacilityName
OutFall
Latitude
Longitude
LrsegId
wqm50cell
COMID
COMIDCB
TblBmpConversionFact
BmpId
LoadTypeId
UnitId
LrsegId
TN
TP
SED
TblLoadsStreamSho
LrsegId
LoadSourceId
AgencyId
LengthFeet
NO3Lbs
NH3Lbs
ORGNLbs
PO4Lbs
ORGPLbs
TSSLbs
TblBmpEmissionReductio
LrsegId
NH3Fraction
NO3Fraction

Variable selection

COLUMN_NAME	DATA_TYPE
AboveRIM	bit
Acres	decimal
Ag	real
AgencyId	tinyint
AnimalId	tinyint
BackoutScenarioId	int
BaseConditionId	int
BmpId	smallint
CBCSOID	smallint
COMID	int
COMIDCB	int
CountyId	smallint
Crop	real
CsoNpdesId	smallint
FacilityName	varchar
FIPS	char
FLO	real
FractionCsoInLrsegForNpdes	real
FractionInLrseg	real
real	
GeographyId	int
HEAT	real
HgmrId	tinyint
LandChangeAmount	real
LandCover	varchar
LandRiverSegment	char
LandSegment	char
LandSegmentGeographyId	int
LandUseAcres	bit

Step 2: Variable Reduction

VARIABLE REDUCTION TECHNIQUE CLUSTERING

How do you simplify your data analysis?

Variable Reduction

- Variable reduction streamlines the modeling process by **minimizing the necessary inputs** for **constructing robust predictive or segmentation models**, **enhancing efficiency and manageability**.

- By **reducing redundant data**, variable clustering **clarifies the fundamental patterns and associations within the dataset's input variables.**

Various Techniques for Variable Reduction

1. Principal Component Analysis (PCA): PCA is a statistical technique that transforms the original variables into a new set of uncorrelated variables ordered so that the first few retain most of the variation present in the original variables.

2. Bayesian variable reduction:

Bayesian variable reduction is a method that leverages Bayesian statistics to pinpoint the most relevant variables, incorporating prior knowledge and data evidence. It is useful for managing large variable sets and model uncertainty.

3. LASSO (Least Absolute Shrinkage and Selection Operator)

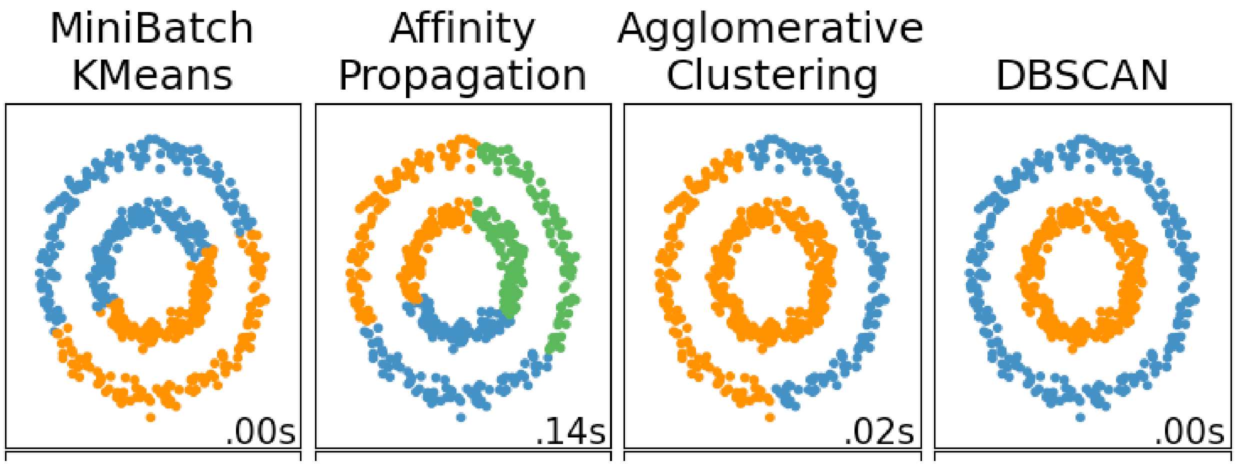
LASSO is a method that combines variable selection and regularization to improve model accuracy and simplicity by penalizing the absolute size of coefficients, reducing some to zero, ideal for datasets with more variables than observations.

4. Ridge Regression

Ridge regression is a technique for analyzing multiple regression data that suffer from multicollinearity. Multicollinearity occurs when predictor variables in a model are highly correlated and can lead to unstable estimates of the regression coefficients. Ridge regression stabilizes these coefficients.

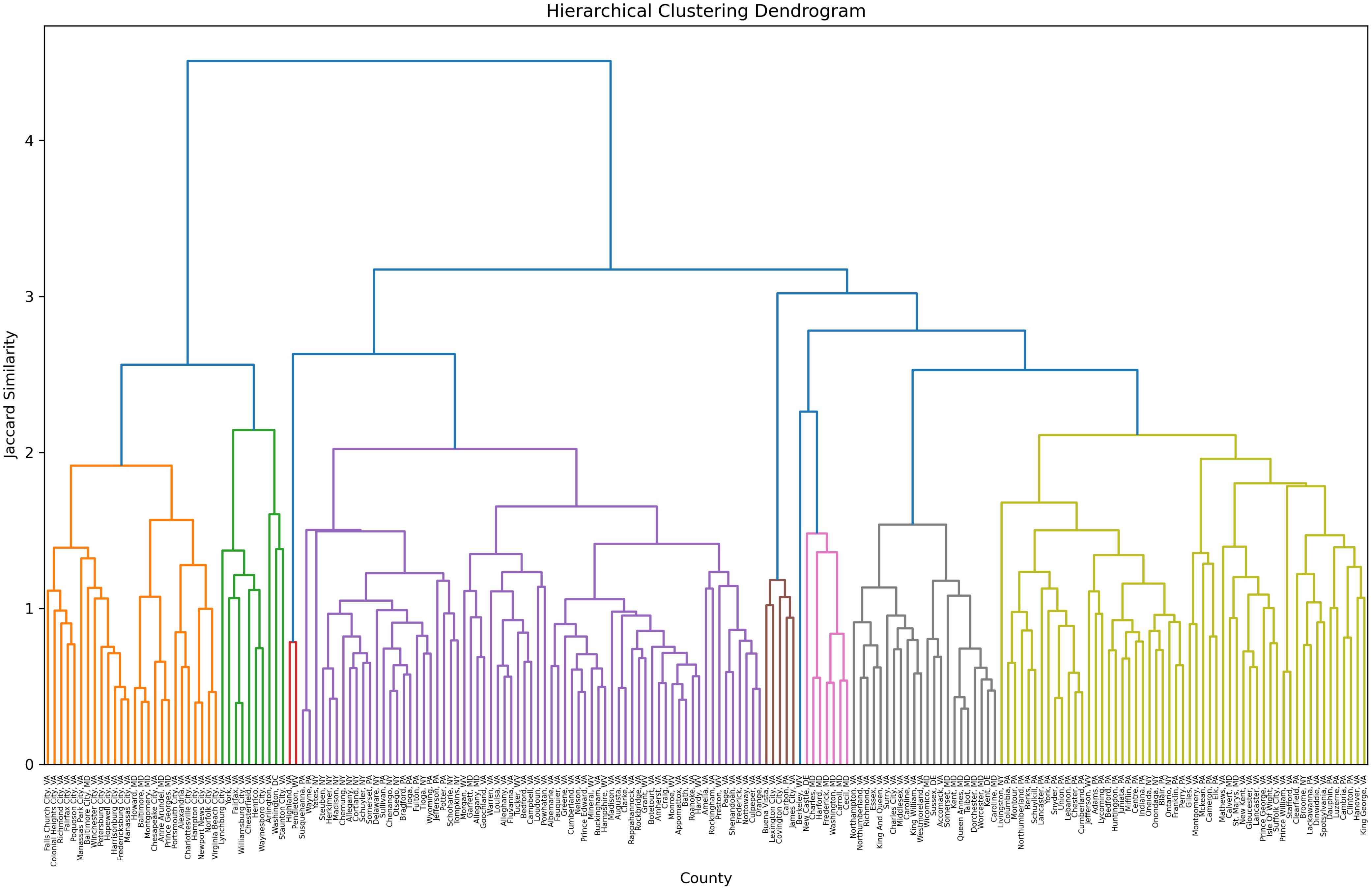
Step 3: Clustering

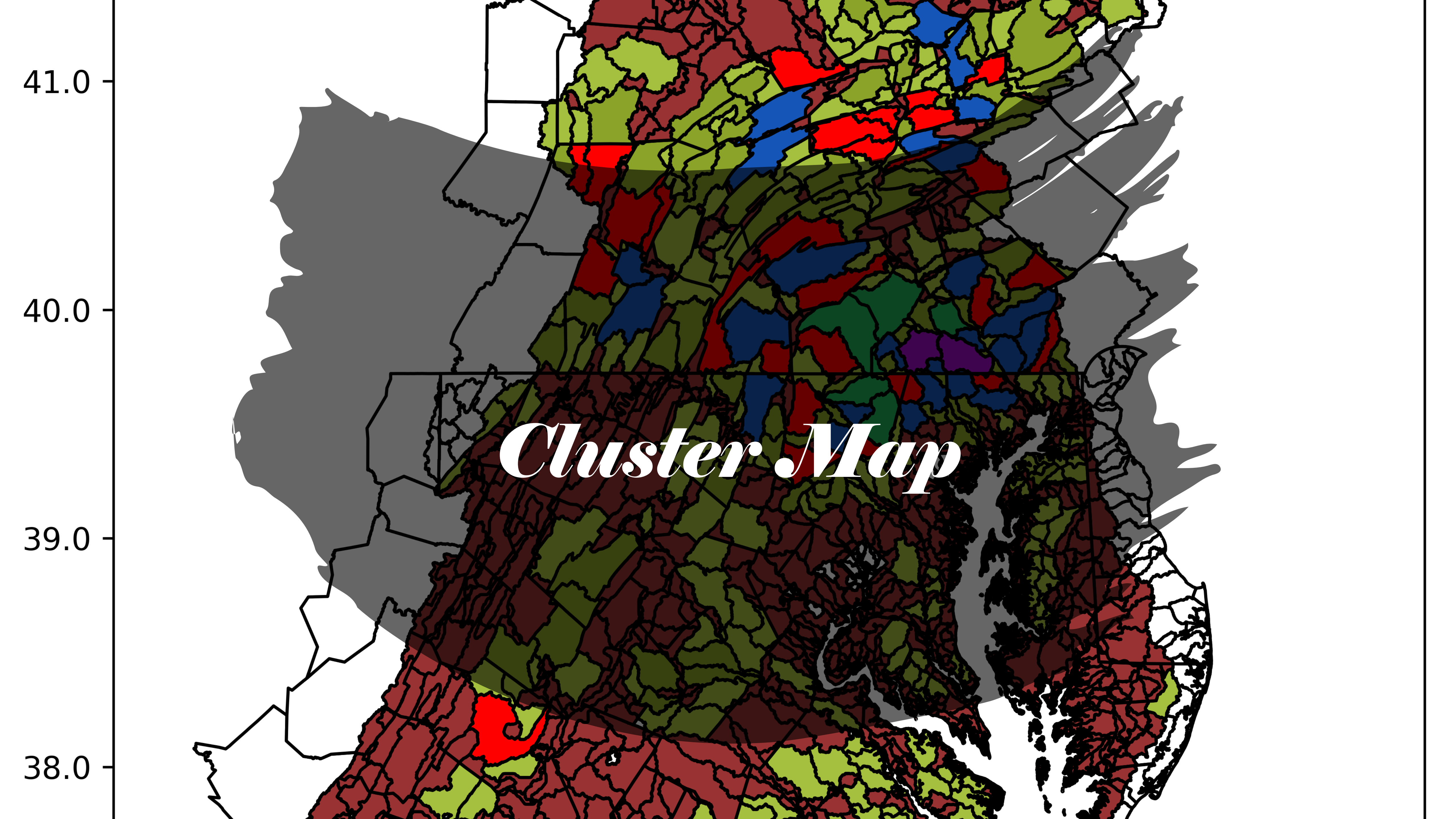
Clustering is an unsupervised/supervised learning method in machine learning and data analysis for grouping similar objects into clusters, widely used for statistical analysis across various fields.



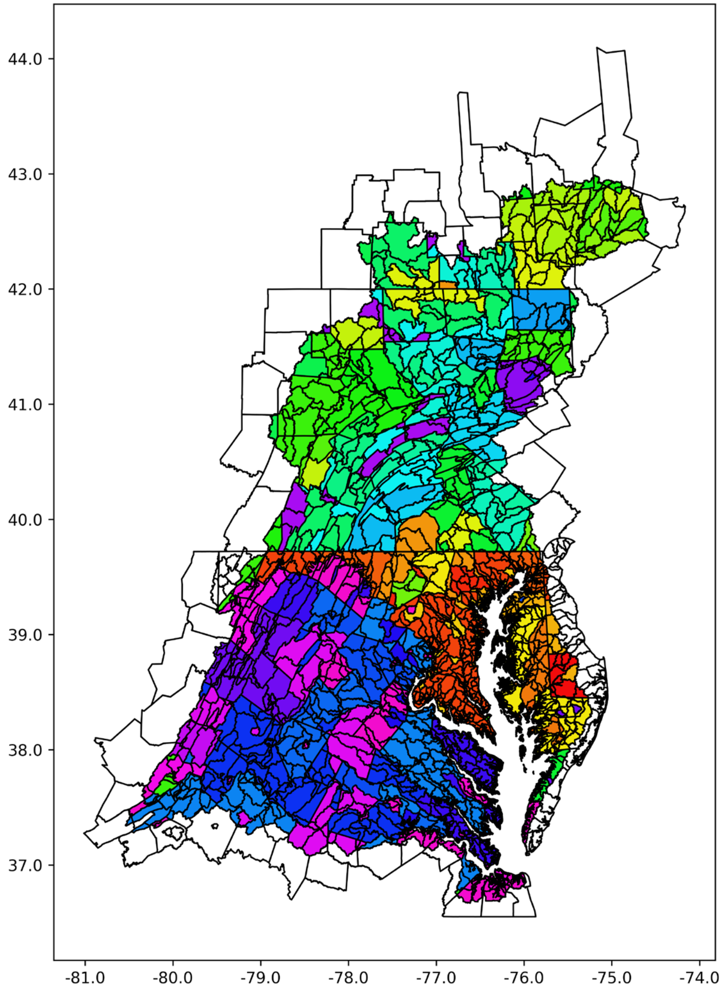
Common Clustering Techniques:

- **<u>K-Means Clustering:</u>** It partitions the dataset into K pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group.
- **<u>Hierarchical Clustering:</u>** This method creates a tree of clusters called a dendrogram, which shows the arrangement of the clusters produced by the corresponding analyses.
- **<u>DBSCAN (Density-Based Spatial Clustering of Applications with Noise):</u>** It groups together points that are closely packed together, marking as outliers the points that lie alone in low-density regions.
- **<u>Affinity Propagation</u>** is determining clusters by identifying representative 'exemplars' through data point messaging.

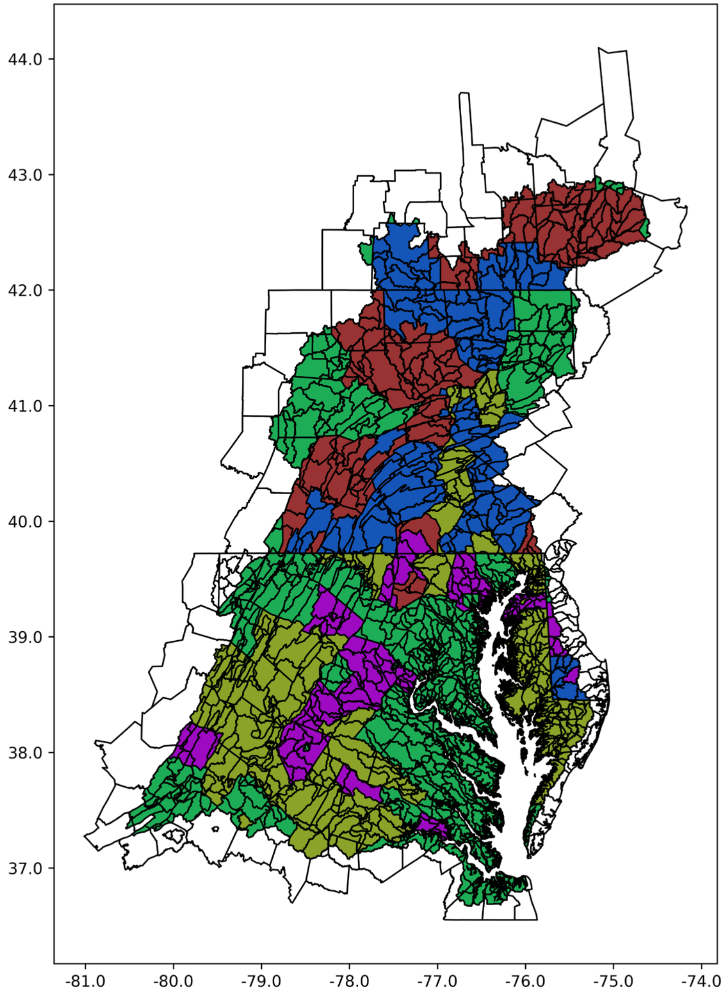

Hierarchical Clustering Dendrogram
Jaccard Similarity
County
0
1
2
3
4



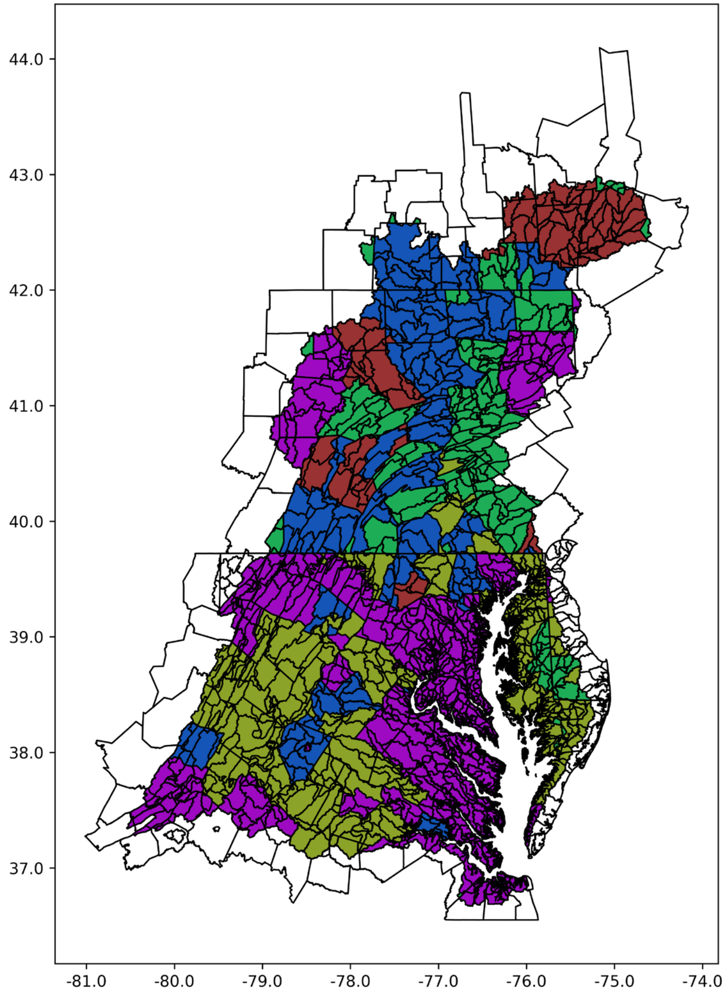
41.0
40.0
39.0
38.0
Cluster Map



Affinity Propagation



Agglomerative



K-means

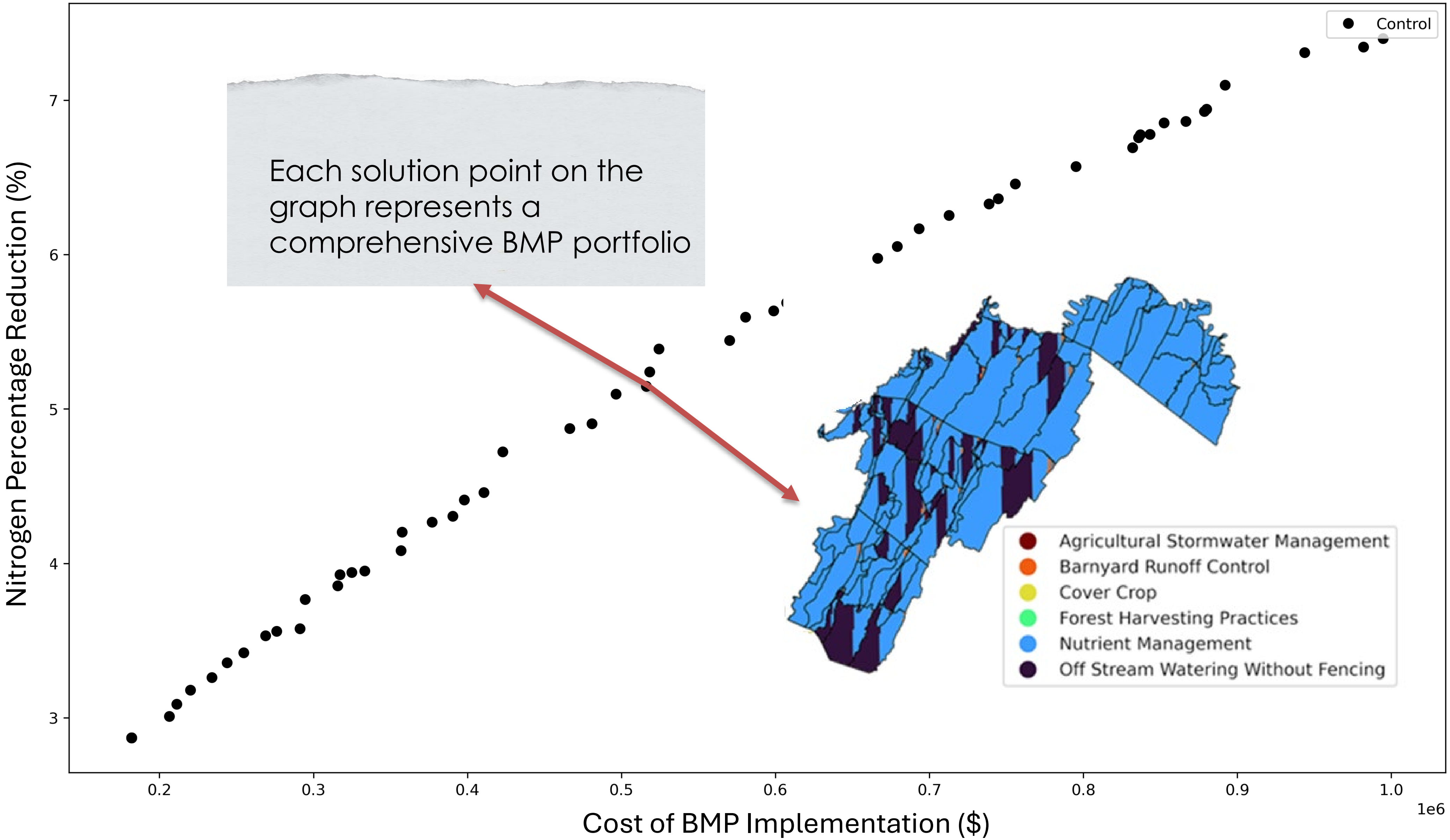
Clustering and Variable Reduction

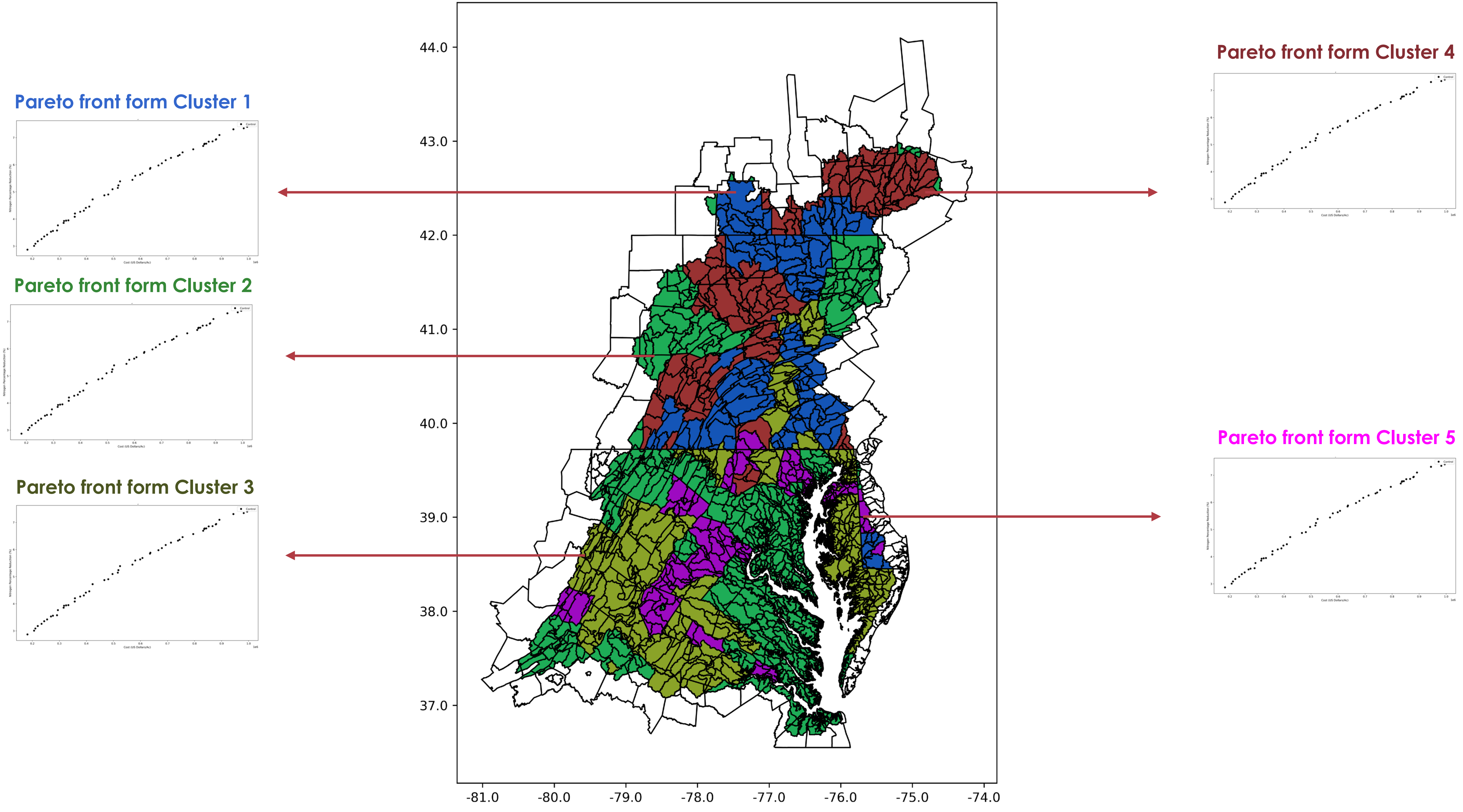
Step 4: Optimization

Optimization

- Perform an analysis using optimization techniques to determine the **BMPs that are selected** most often in **land river segment** and **identify their specific features** or characteristics.

Optimization




Pareto front form Cluster 1
Pareto front form Cluster 2
Pareto front form Cluster 3
Pareto front form Cluster 4
Pareto front form Cluster 5
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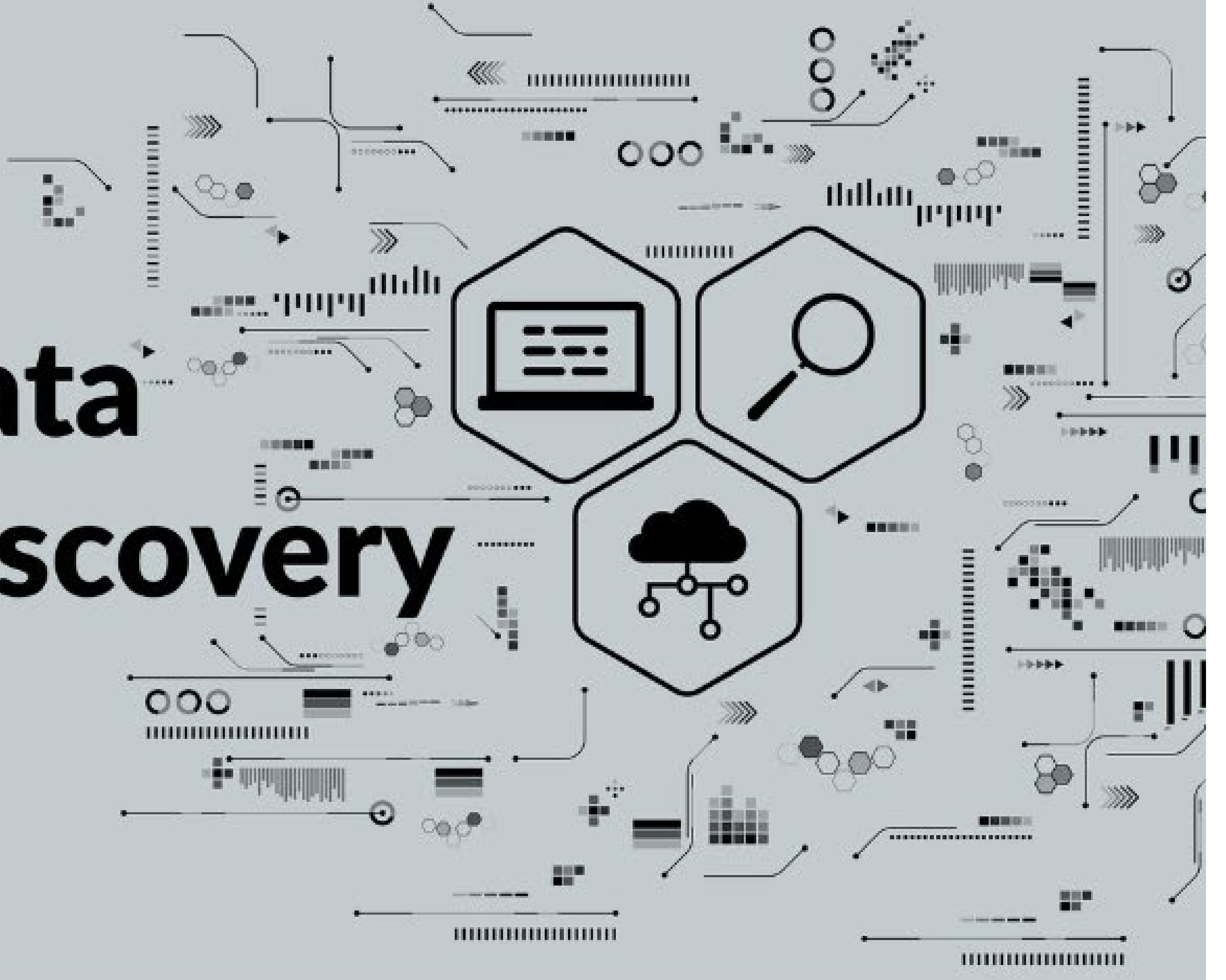
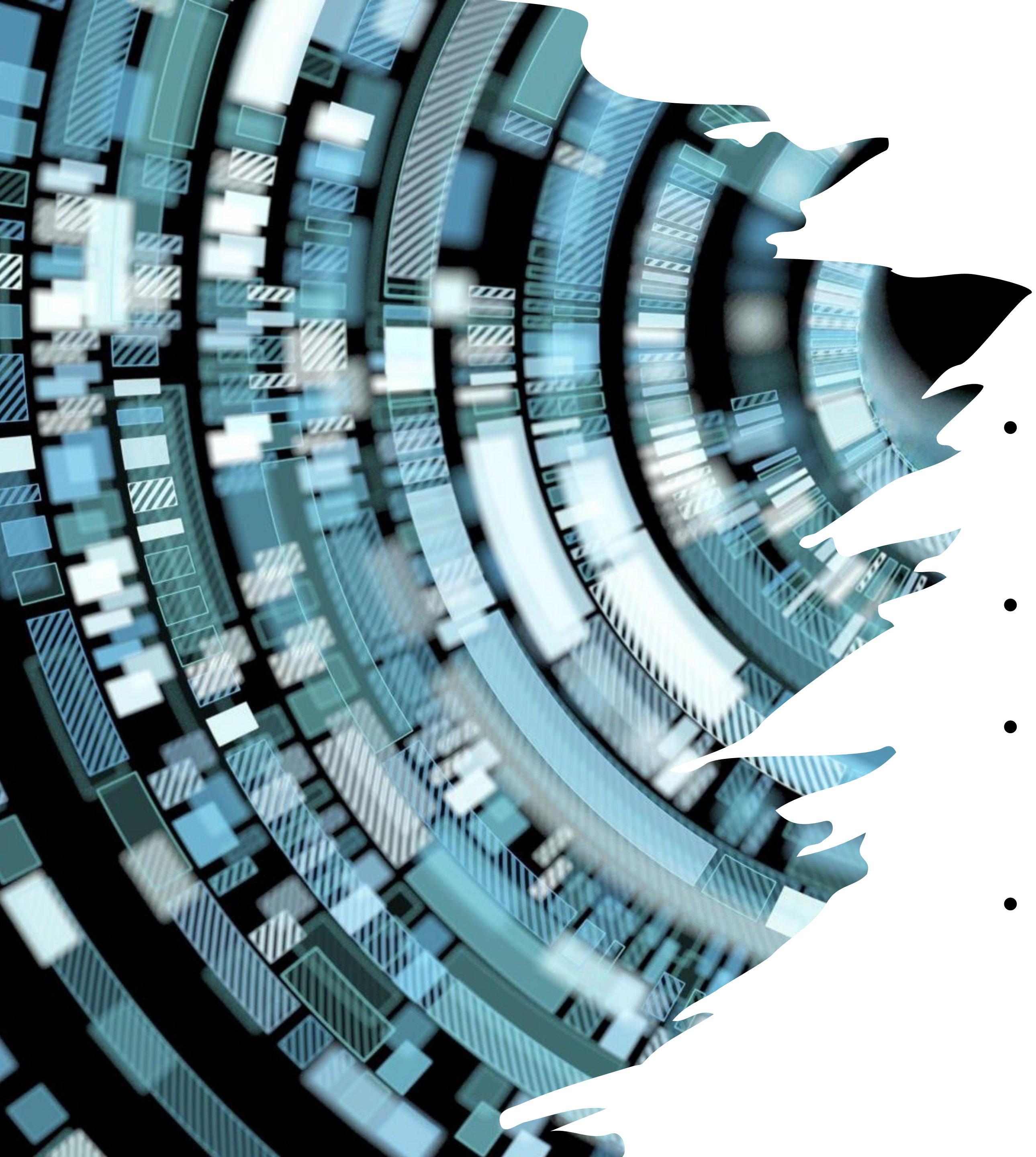
-74.0

Step 5: Data Discovery



Data Discovery

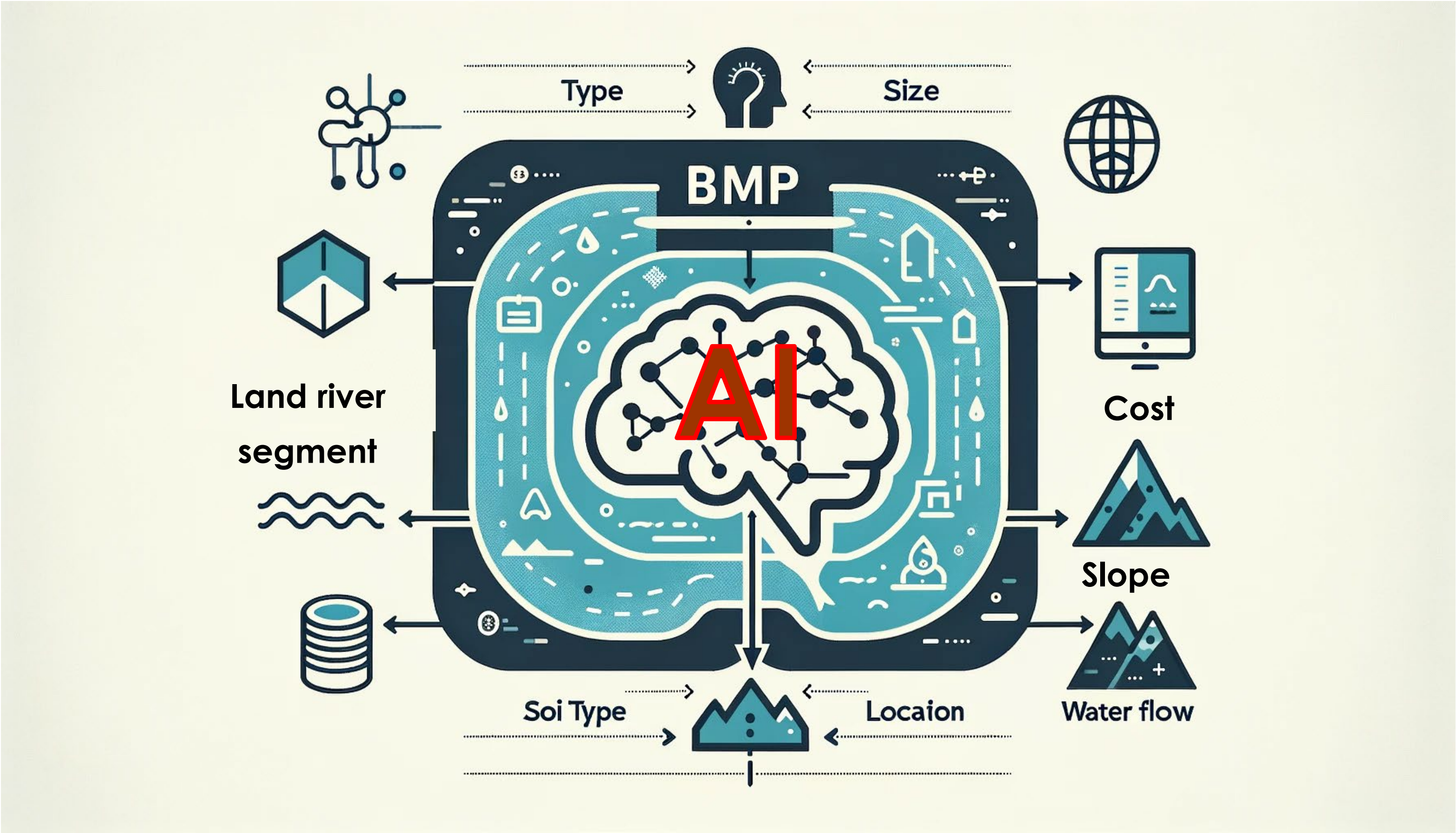
Employ **artificial intelligence** methods to recognize the **relationships between clustering, variable combinations, land river segments, and BMP selection.**



Artificial Intelligence

- **Machine Learning Approaches** (e.g., Random Forests, support vector machines, deep learning).
- **Optimization and Search Algorithms** (e.g., Genetic Algorithms).
- **Bayesian Networks and Probabilistic Models** (e.g., Markov chain Monte Carlo and Gaussian Processes).
- **Decision Support Systems** (e.g., Automated Decision Making and Cognitive Computing).

Connecting BMP and Land River Segment Characteristics



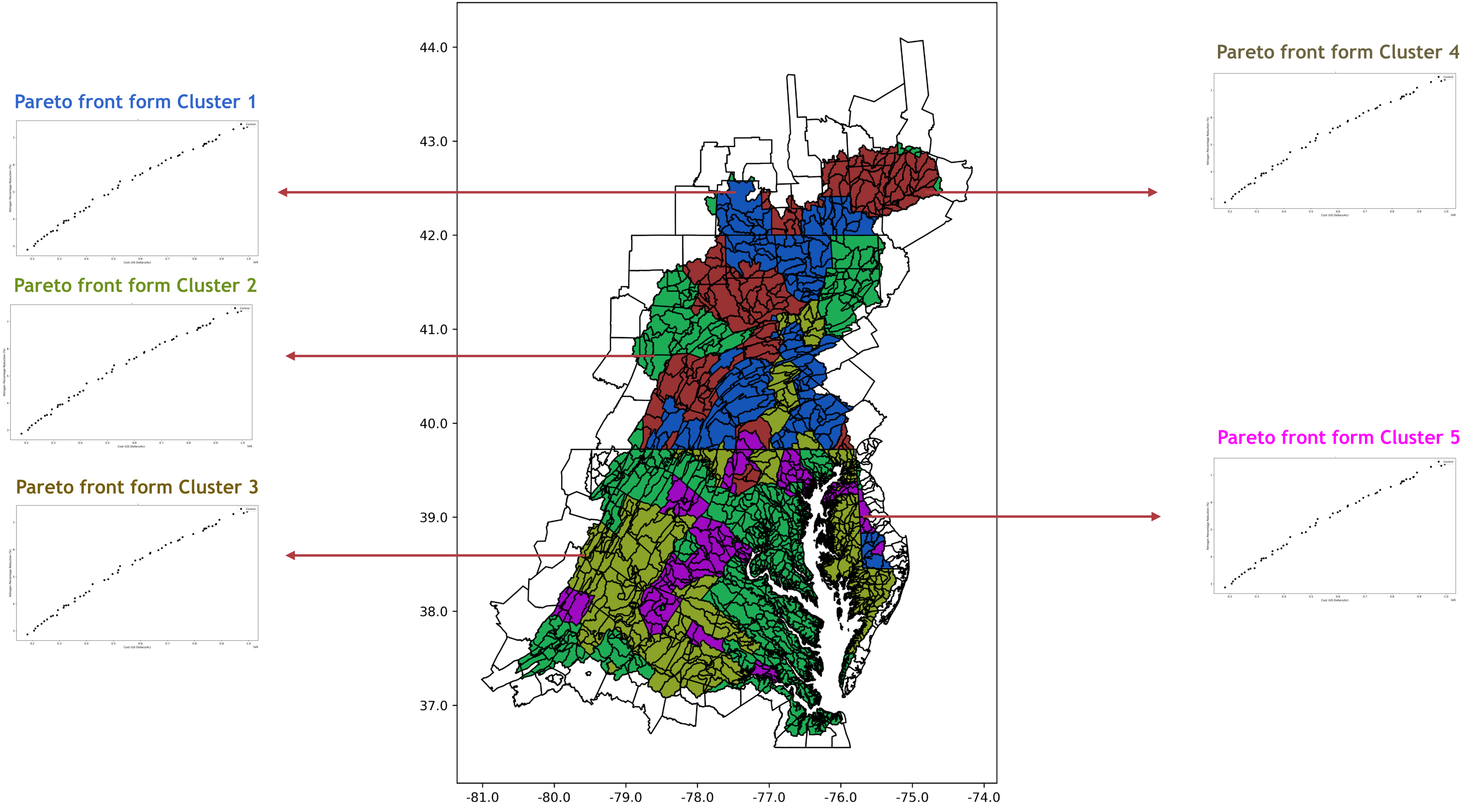
Connecting BMP and Land River Segment Characteristics

Employ	Employ **artificial intelligence** to reveal **patterns** between **environmental parameters**.
Determine	Determine the **most effective pairings of parameters** and **clustering techniques** to enhance watershed management strategies.
Use	Use these insights to **streamline BMP implementation plans** across the **Chesapeake Bay watershed**.

Step 7: Test and Validation

Test & Validation

The **outcomes** from this section will be **tested in different areas** within the Chesapeake Bay watershed to **confirm their reliability and applicability**.



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Pareto front form Cluster 3
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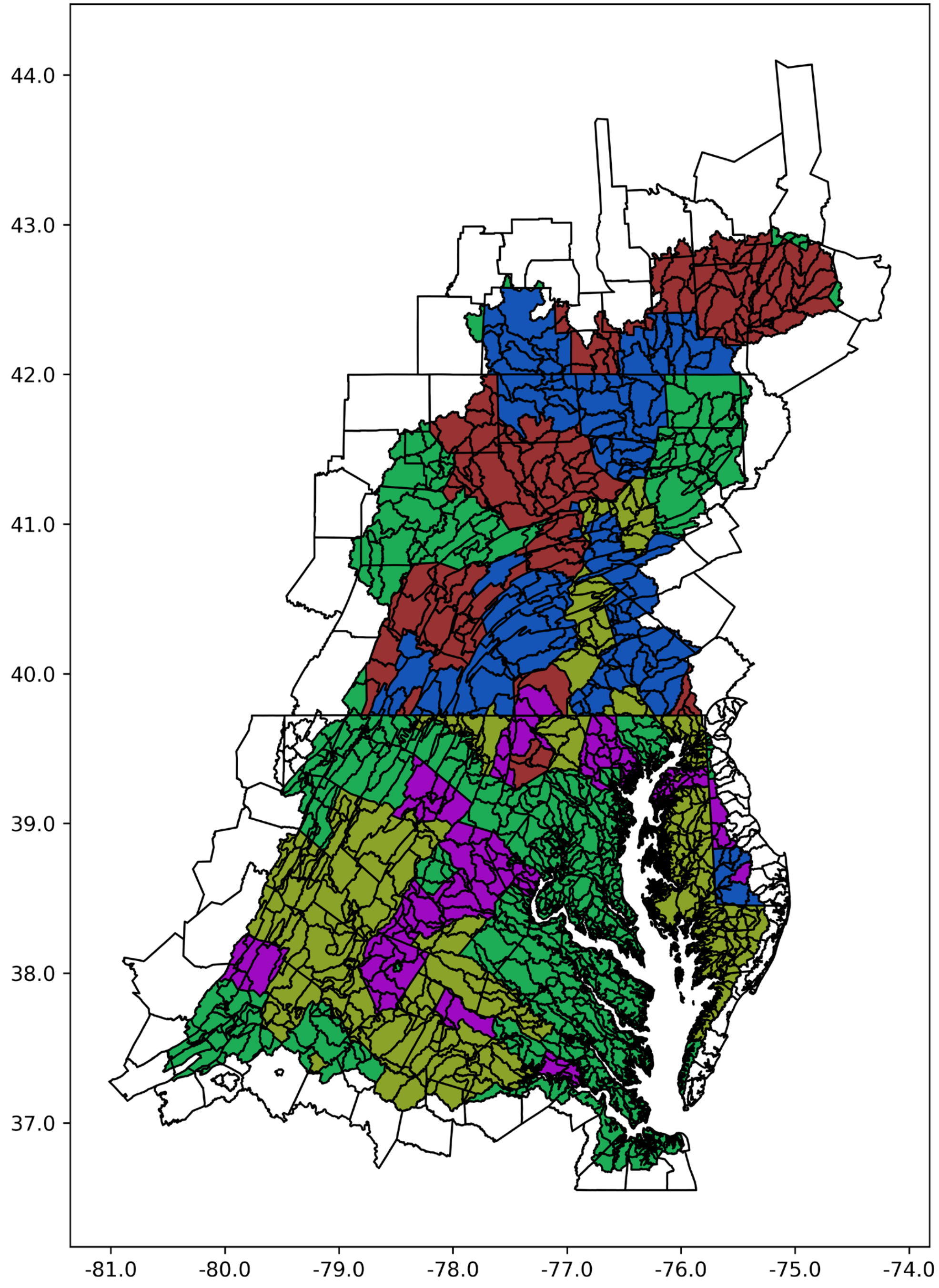

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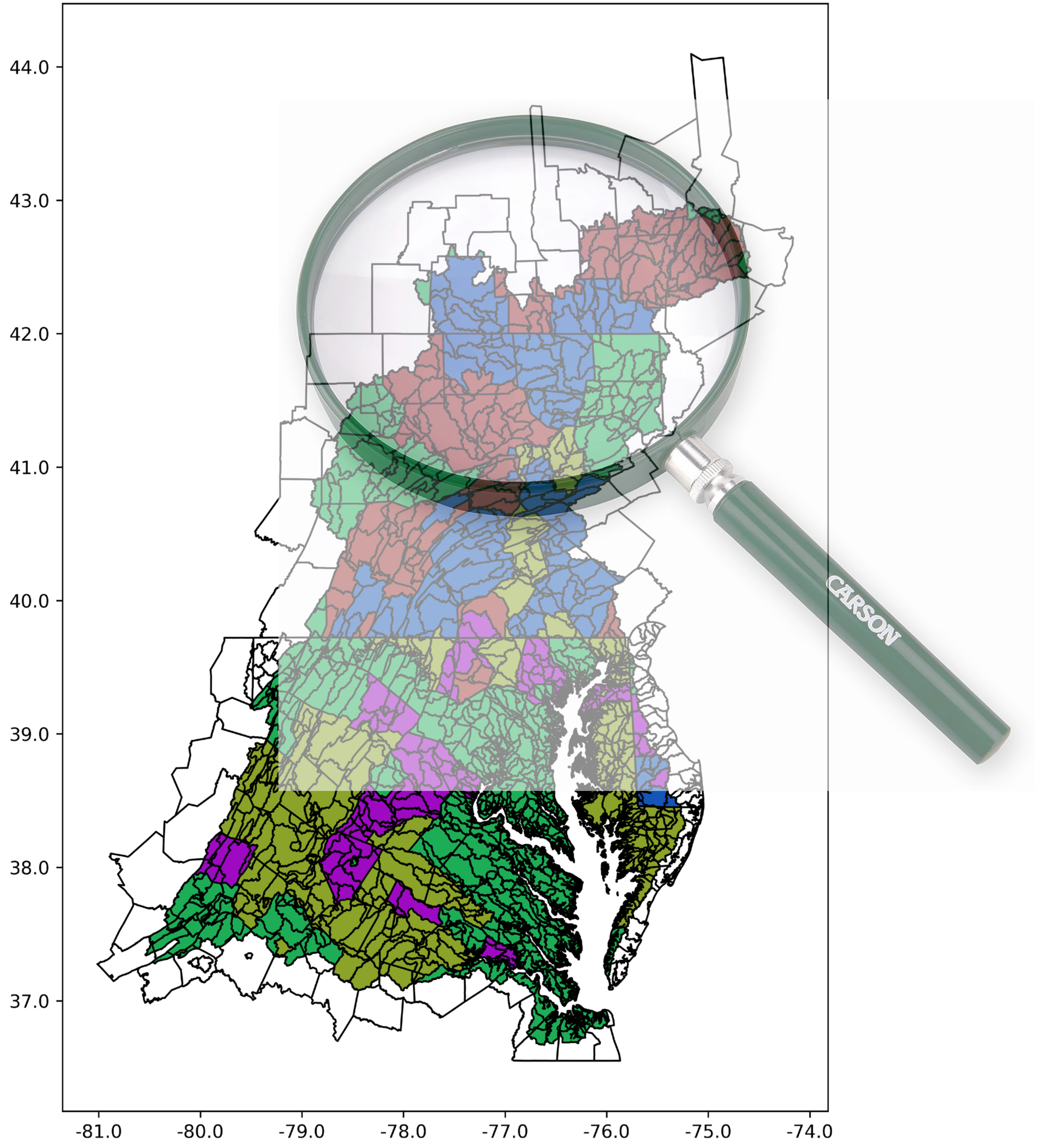
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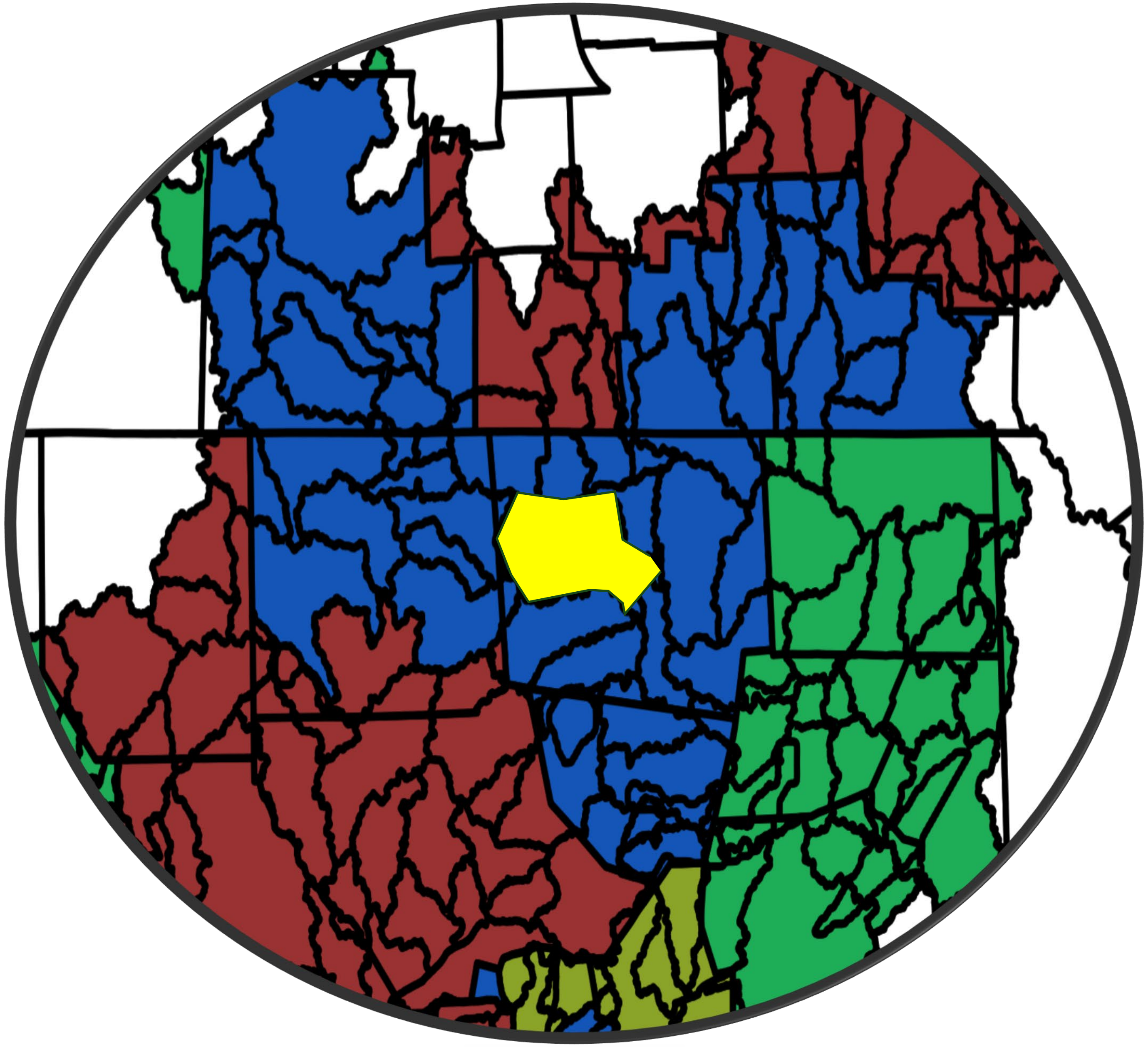
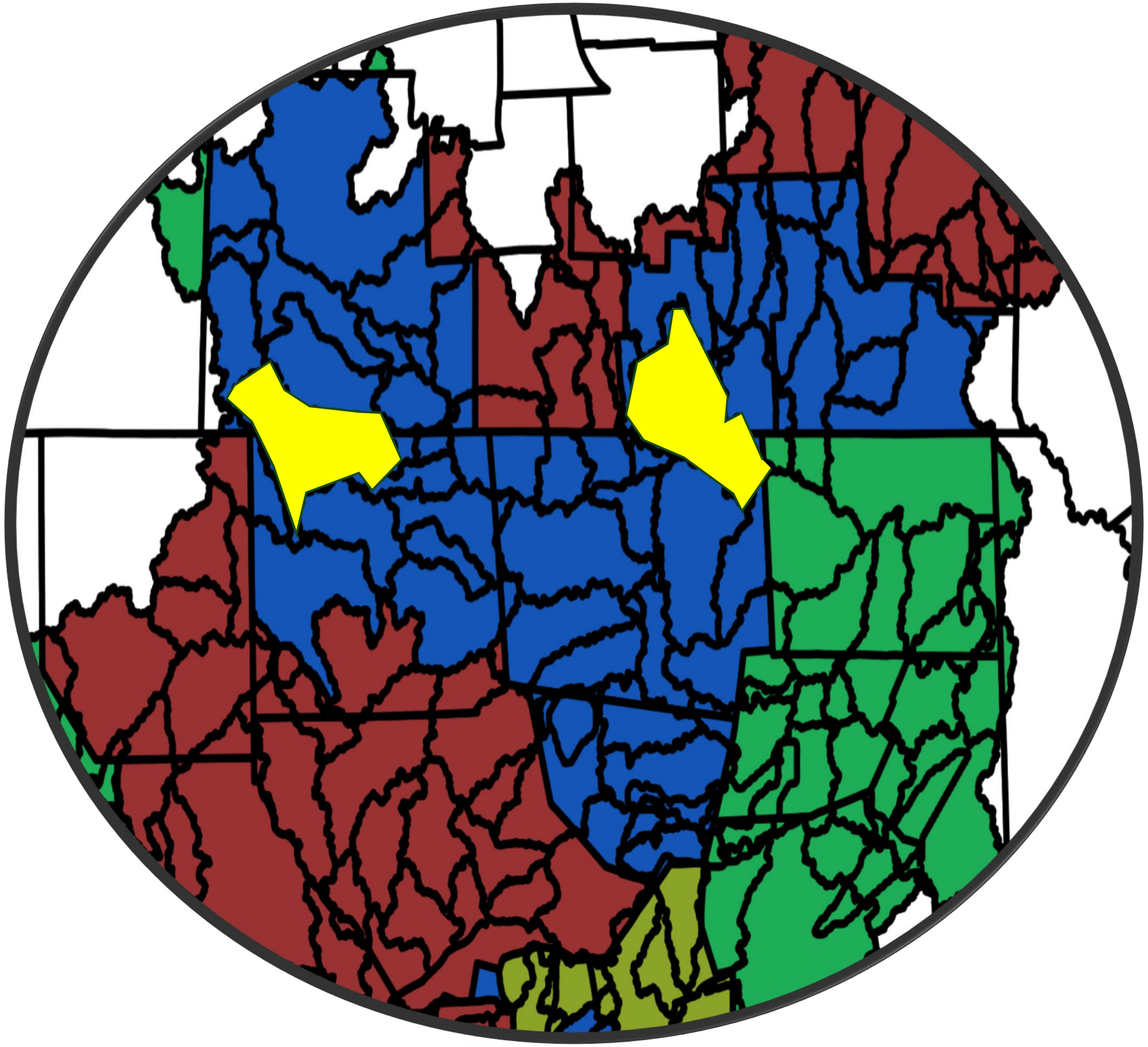
CARSON





Interactive Optimization & Decision making

1 Scenario Info — 2 Loads — 3 BMP Selection — 4 Update Costs — 5 BMP Constraint — 6 BMP Constraint Advanced

Scenario Info

SCENARIO NAME:	JEFFERSON
COUNTIES:	JEFFERSON, WV
BASE SCENARIO:	NO BMP
BASE CONDITION:	2019 14
SCENARIO TYPE:	OFFICIAL BMPS
COST PROFILE:	WATERSHED
HISTORICAL CROP NEED SCENARIO:	6608
POINT SOURCE DATA SET:	NO ACTION

The users can fine-tune their expected load targets, BMPs, costs, or constrain the use of BMPs using a 6 steps input flow. The first step shows information regarding the scenario.

The user can indicate a maximum removal percentage for loads. The user can modify any of the percentage or the actual load.

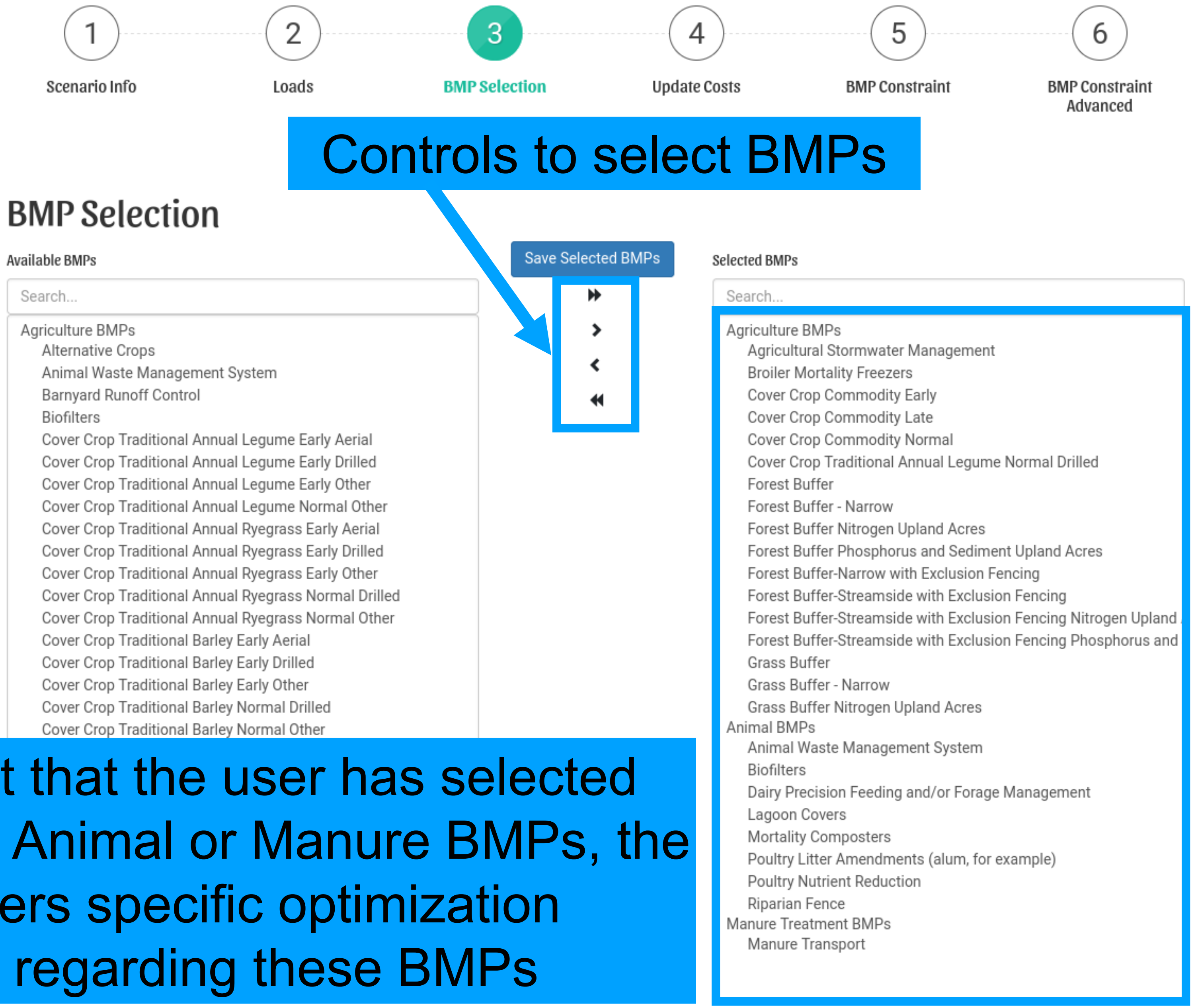
1 Scenario Info — 2 **Loads** — 3 BMP Selection

Loads

Load	Initial Load	Removal Percentage	Expected load
Nitrogen	1,296,058.06	30.00 %	907240.64 lb
Phosphorus	91,071.79	0.00 %	91071.79 lb
Sediments	148,489,139.86	0.00 %	148489139.86 lb

TOTAL DOLLARS FOR BMP IMPLEMENTATION:

TOTAL ACRES ALLOCATED TO BMP: 145,790.88 ACRES 100.00 % 145790.88 Acres



Controls to select BMPs

Efficiency BMPs

Land Conversion BMPs

Animal BMPs

Manure Transport

When we detect that the user has selected Land Conversion, Animal or Manure BMPs, the system triggers specific optimization procedures regarding these BMPs

1 Scenario Info — 2 Loads — 3 BMP Selection — **4 Update Costs** — 5 BMP Constraint — 6 BMP Constraint Advanced

Update BMP Total Cost Per Unit

BMP: Agricultural Stormwater Management

TOTAL COST PER UNIT

UNIT

NEW TOTAL COST PER UNIT

Add

The user can modify the cost per unit that the optimization approach will use to perform the search.

#	BMP	Original Cost per Unit ($)	Updated Cost per Unit ($)
1	Cover Crop Commodity Early	77.87	10.0

1 Scenario Info | 2 Loads | 3 BMP Selection | 4 Update Costs | **5 BMP Constraint** | 6 BMP Constraint Advanced

BMP Constraint

BMP: Agricultural Stormwater Management

TOTAL COST PER UNIT:

UNIT:

Constraint: 0.00 Units 0.00 Cost ($)

Add

#	BMP	Maximum Allocation (Units)	Maximum Allocation ($)
1	Alternative Crops	100.00	10,919.00

The user can indicate the maximum allocation of BMPs

1 Scenario Info | 2 Loads | 3 BMP Selection | 4 Update Costs | 5 BMP Constraint | 6 BMP Constraint Advanced

BMP Constraint (Advanced)

Add your preferences:

Developed | Septic | Natural | Manure Treatment | Animal | Land Conversion | Agriculture

Agriculture

LAND RIVER SEGMENT

N54037PU6_4080_4180

AGENCY

Non-Federal

LOAD SOURCE

Ag Open Space

BMP GROUPS

Group 1

The user can specify the desire allocation of a BMP in certain LRS-Agency-LoadSource

BMP list

BMP Group Max Amount (acres): 8.59

1. Soil Conservation and Water Quality Plans

Min amount | Max amount

Add

#	LRSeg	Agency	Load Source	Bmp	Min Amount	Max Amount
1	N54037PU6_4080_4180	Non-Federal	Ag Open Space	Soil Conservation and Water Quality Plans	0	5

Executions (Results)

\+ Search Clear

Id	Cost	Nitrogen	Phosphorus	Sediments
205	$ 635,868	1,186,825 lbs	72,233 lbs	134,106,494 lbs
206	$ 1,120,260	1,164,530 lbs	72,036 lbs	132,555,760 lbs
207	$ 718,151	1,179,864 lbs	74,280 lbs	134,535,442 lbs
208	$ 1,167,	[illegible]	[illegible]	[illegible]
209	$ 724,83	[illegible]	[illegible]	[illegible]
210	$ 784,74	[illegible]	[illegible]	[illegible]
211	$ 1,314,	[illegible]	[illegible]	[illegible]
212	$ 543,83	[illegible]	[illegible]	[illegible]
213	$ 819,504	1,168,267 lbs	74,826 lbs	134,406,563 lbs
214	$ 482,654	1,195,935 lbs	79,396 lbs	139,129,245 lbs
215	$ 1,006,390	1,164,717 lbs	72,440 lbs	132,520,354 lbs
216	$ 702,553	1,184,550 lbs	78,024 lbs	137,501,963 lbs

The optimization approach finds a set of scenarios in a single execution. The users can explore the obtained solutions.

BMP Results BMP

SEARCH:

	#	BMP	Acres	Cost	Mode	Min Amount	Max Amount
☐	1	Off Stream Watering Without Fencing	12,827.78	12,956.06	ACRES / COST	0	12,827.78
☐	2	Nutrient Management Plan	0.00	0.00	ACRES / COST	0	0.00
☐	3	Cover Crop Traditional Rye Early Drilled	897.37	69,878.26	ACRES / COST	0	897.37
☐	4	Nutrient Management N Timing	8[illegible]	[illegible]	[illegible]	[illegible]	[illegible]6.45
☐	5	Nutrient Management N Rate	4[illegible]	[illegible]	[illegible]	[illegible]	[illegible]5.95
☐	6	Barnyard Runoff Control	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]7
☐	7	Nutrient Management Plan High Risk Lawn	26,538.60	52,811.82	ACRES / COST	0	26,538.60
☐	8	Denitrifying Ditch Bioreactors	6,010.65	193,422.72	ACRES / COST	0	6,010.65

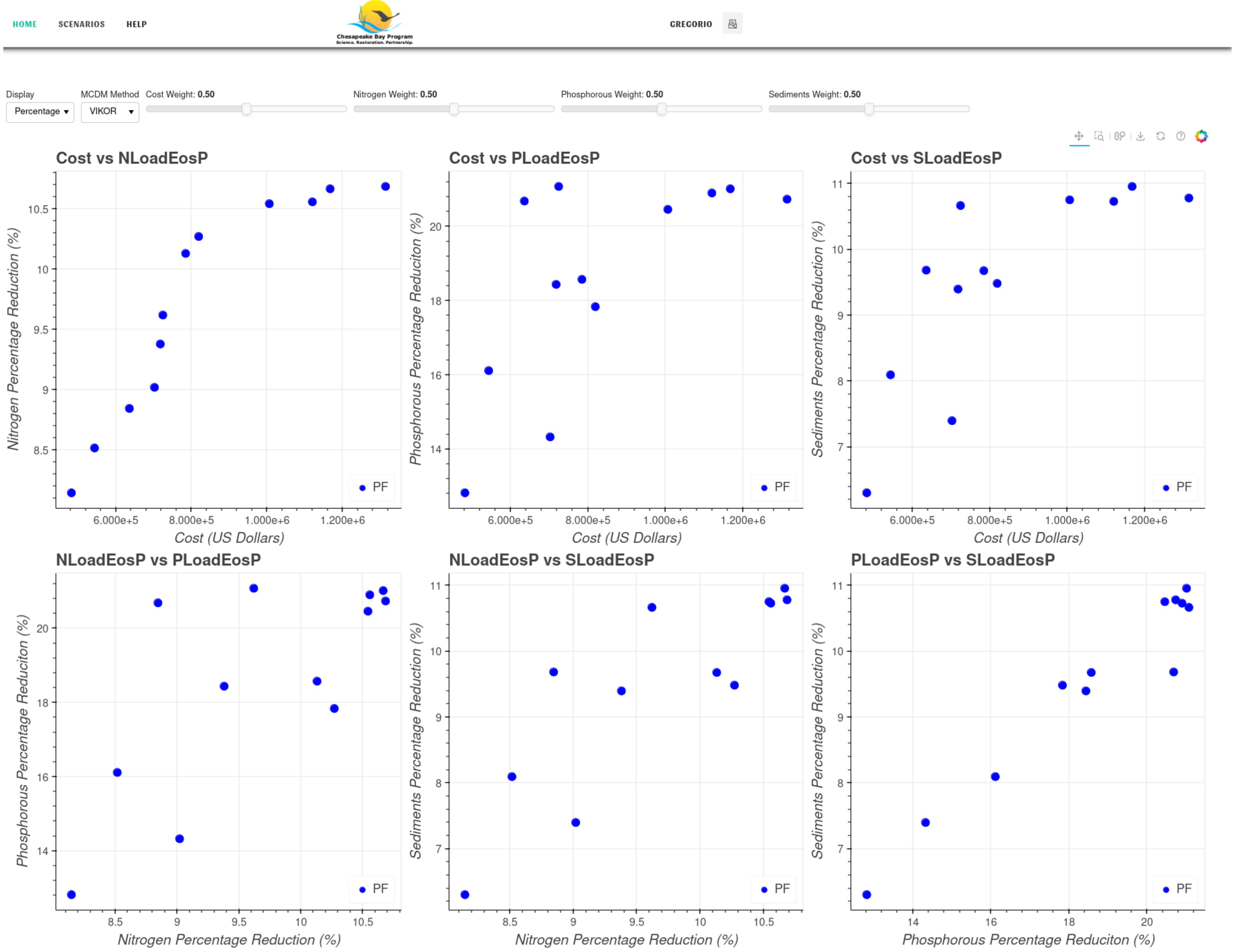
It is possible to inspect the results, and to set up new boundaries for BMPS to use in future executions.

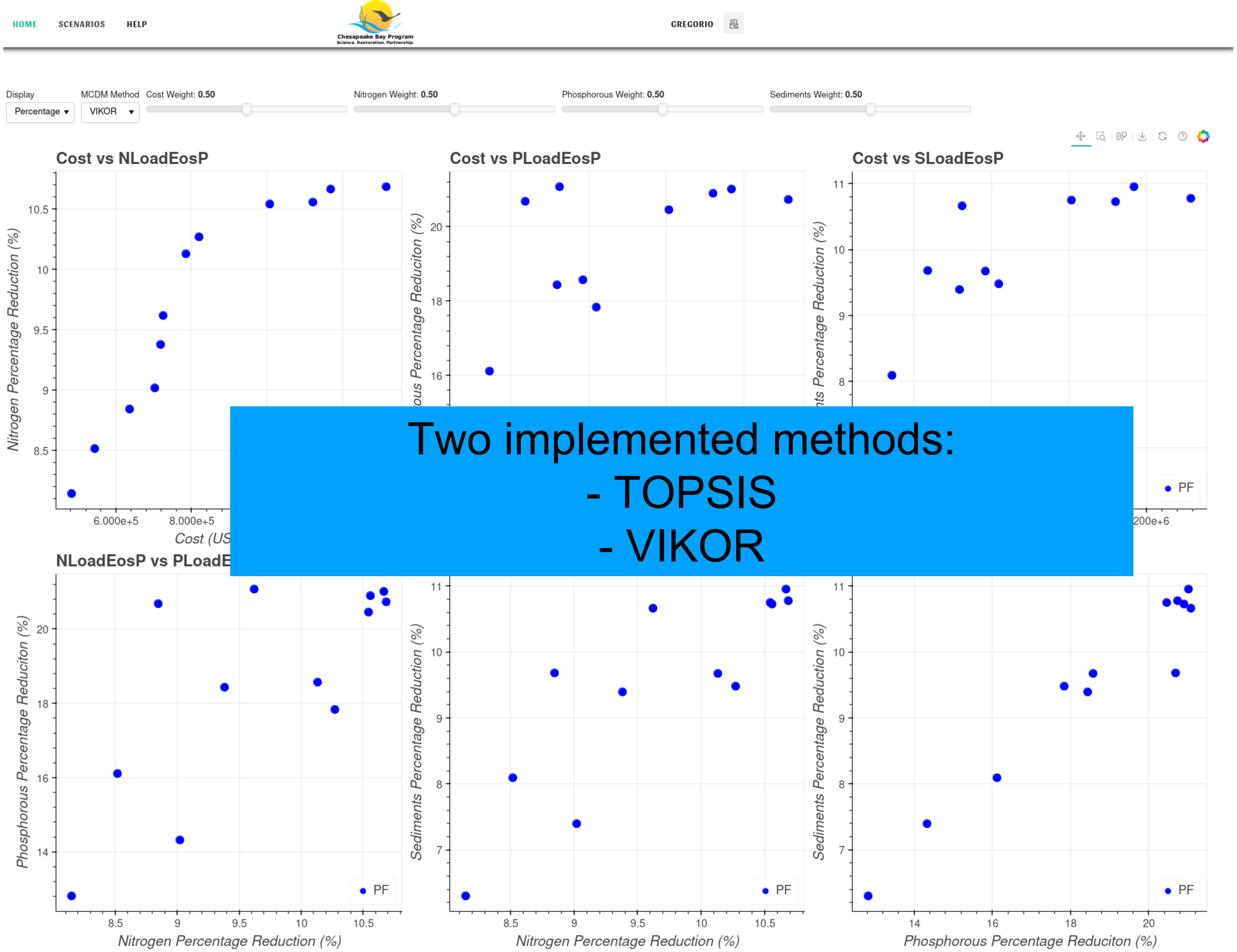
Detailed BMP Results

SEARCH:

	#	Land-River-Segment	Agency	Load Source	Bmp	Acres	Cost ($)	Mode	Min Amount	Max Amount
☐	1	N54037PU6_4180_4150	Non-Federal	Grain without Manure	Denitrifying Ditch Bioreactors	1,300.10	41,837.26	◉ FIXED ○ ACRES ○ COST	0	1,300.1
☐	2	N54037PU2_3900_3750	Non-Federal	Grain without Mar	Denitrifying Ditch	50.66	1,630.32	◉ FIXED ○ ACRES	0	50.66
☐	3	N54037PU6_3750_3752	Non-Federal	Grai with Mar	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	259.31
☐	4	N54037PU6_4080_4180	Non-Federal	Grain without Manure	Denitrifying Ditch Bioreactors	123.85	3,985.36	◉ FIXED ○ ACRES ○ COST	0	123.85
☐	5	N54037PU2_4220_3900	Non-Federal	Grain without Manure	Denitrifying Ditch Bioreactors	1,299.34	41,812.71	◉ FIXED ○ ACRES ○ COST	0	1,299.3
☐	6	N54037PU6_3752_4080	Non-Federal	Grain without	Denitrifying Ditch	8.27	266.27	◉ FIXED ○ ACRES	0	8.27

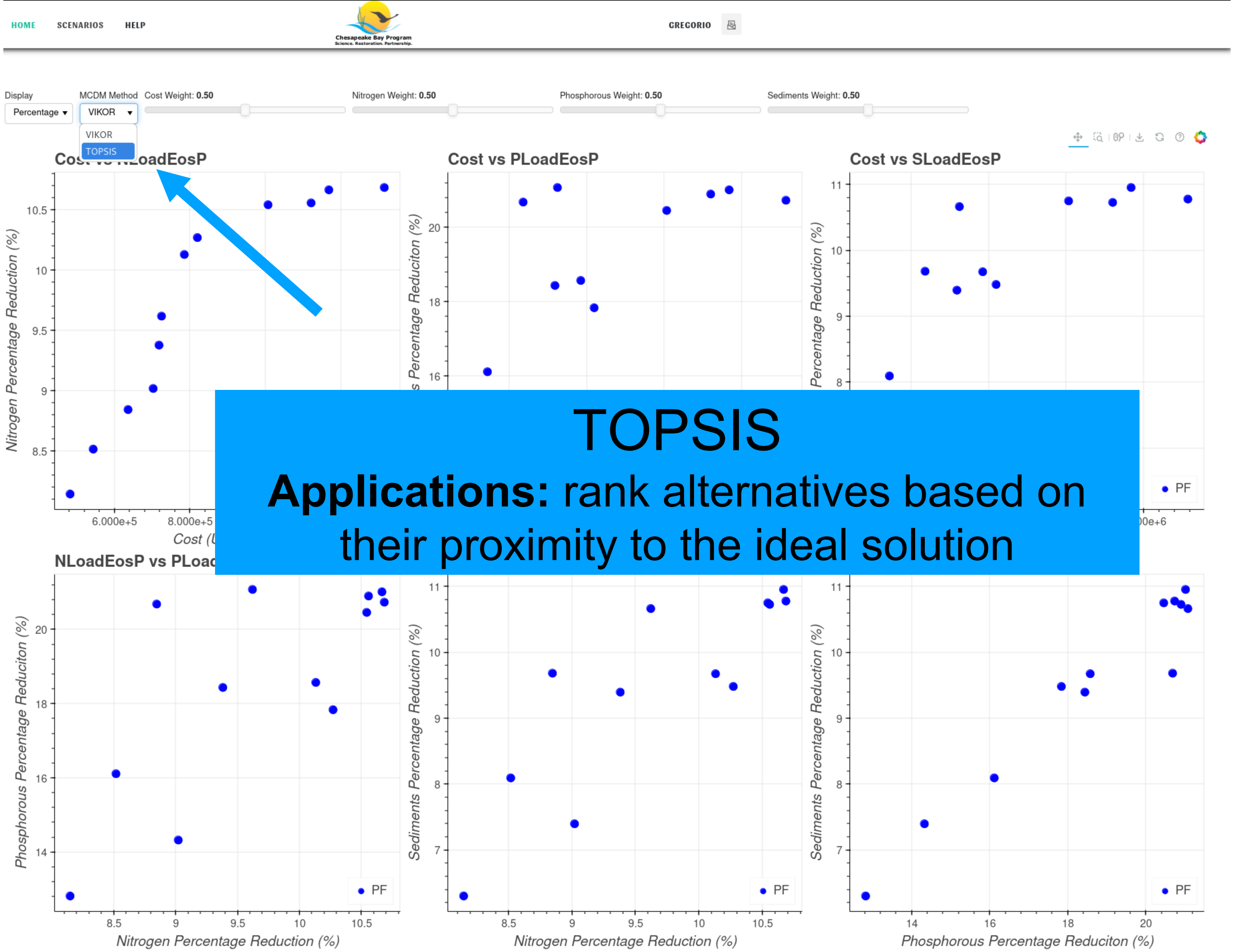
Users can check each proposed BMP, and set up constraints for future runs.


HOME
SCENARIOS
HELP
Chesapeake Bay Program
Science. Restoration. Partnership.
GREGORIO
Display
Percentage
MCDM Method
VIKOR
Cost Weight: 0.50
Nitrogen Weight: 0.50
Phosphorous Weight: 0.50
Sediments Weight: 0.50
Cost vs NLoadEosP
Cost vs PLoadEosP
Cost vs SLoadEosP
NLoadEosP vs PLoadEosP
NLoadEosP vs SLoadEosP
PLoadEosP vs SLoadEosP
Cost (US Dollars)
Nitrogen Percentage Reduction (%)
Phosphorous Percentage Reduciton (%)
Sediments Percentage Reduction (%)
Phosphorous Percentage Reduciton (%)
6.000e+5
8.000e+5
1.000e+6
1.200e+6
PF



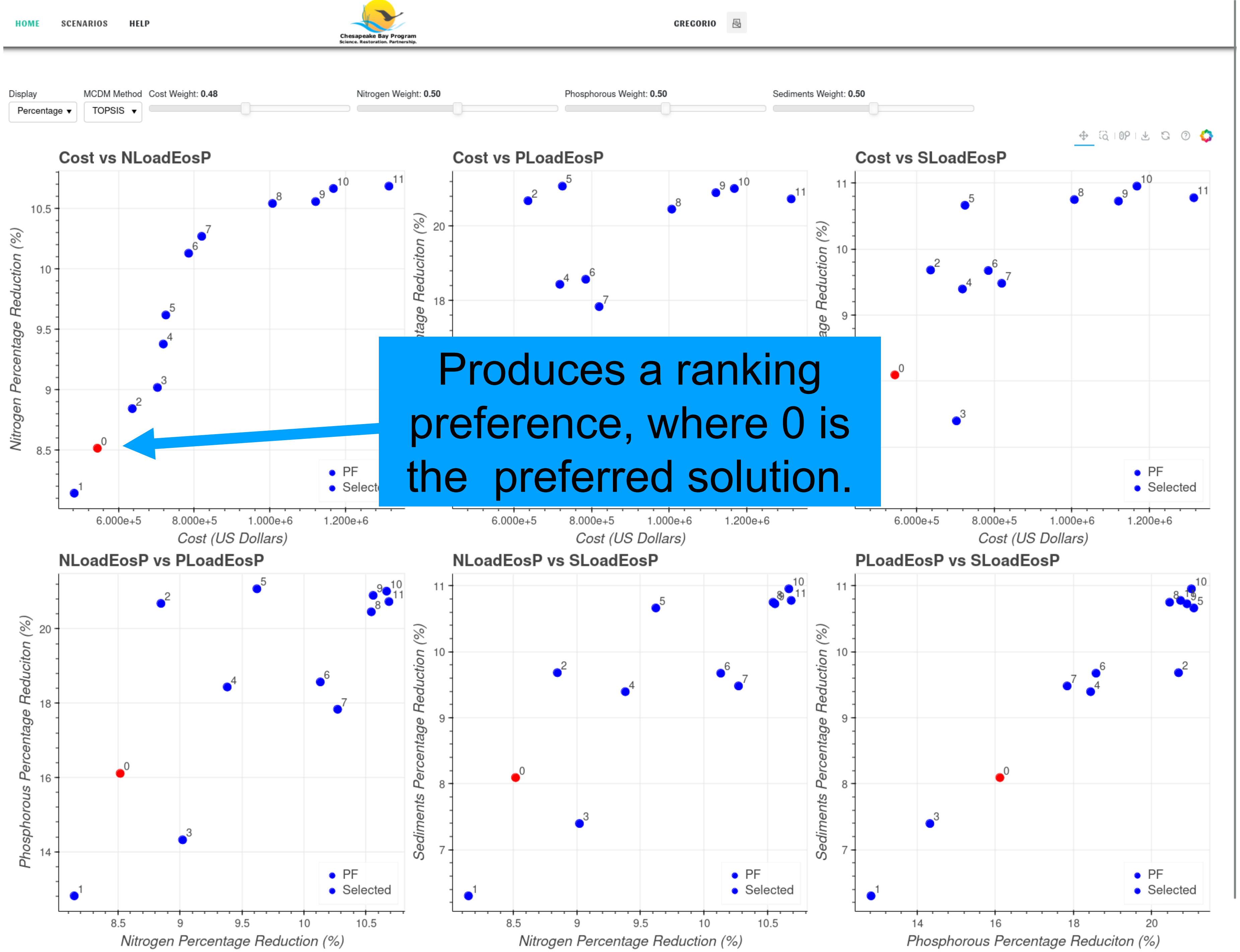
Two implemented methods:

- TOPSIS
- VIKOR



TOPSIS

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


HOME
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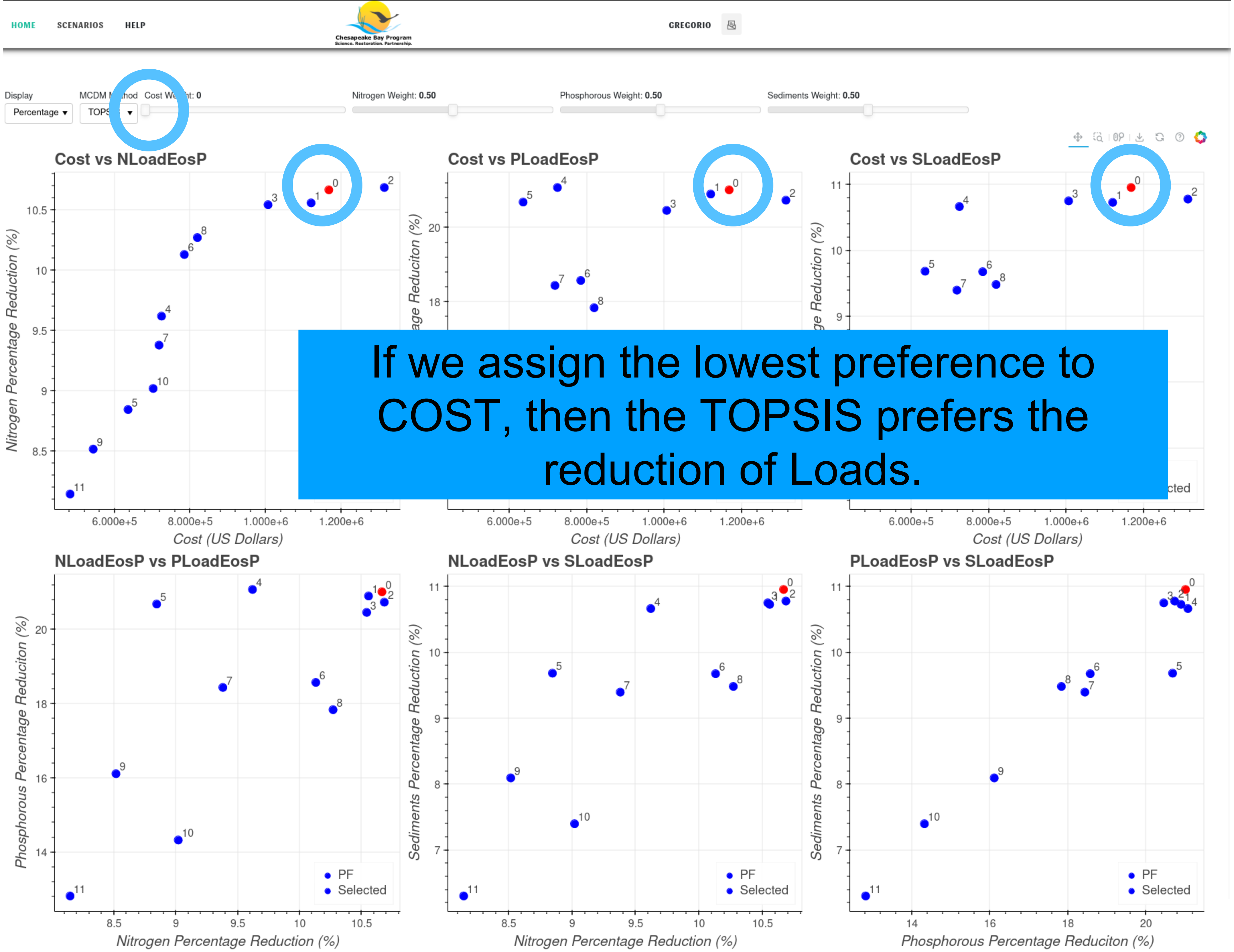
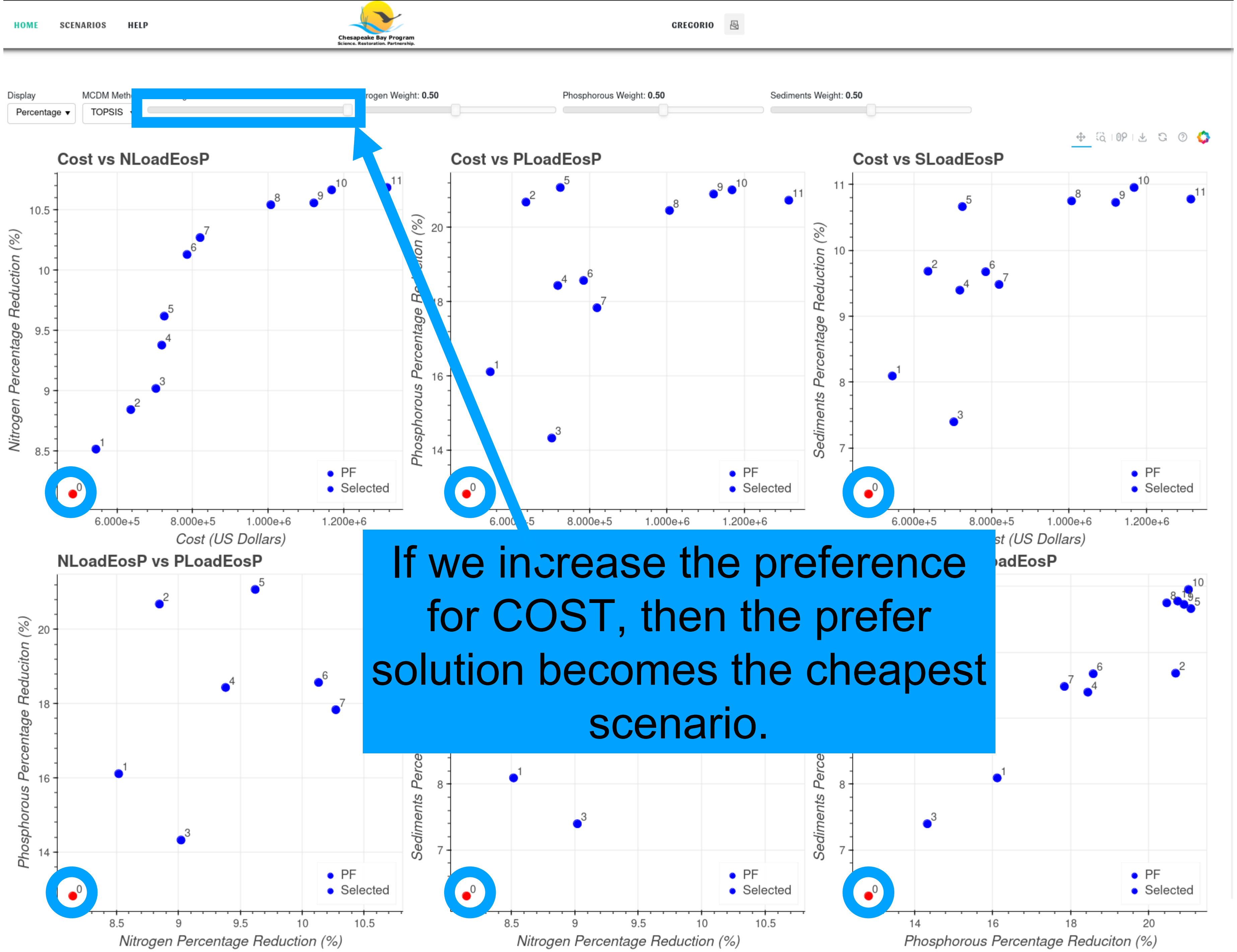
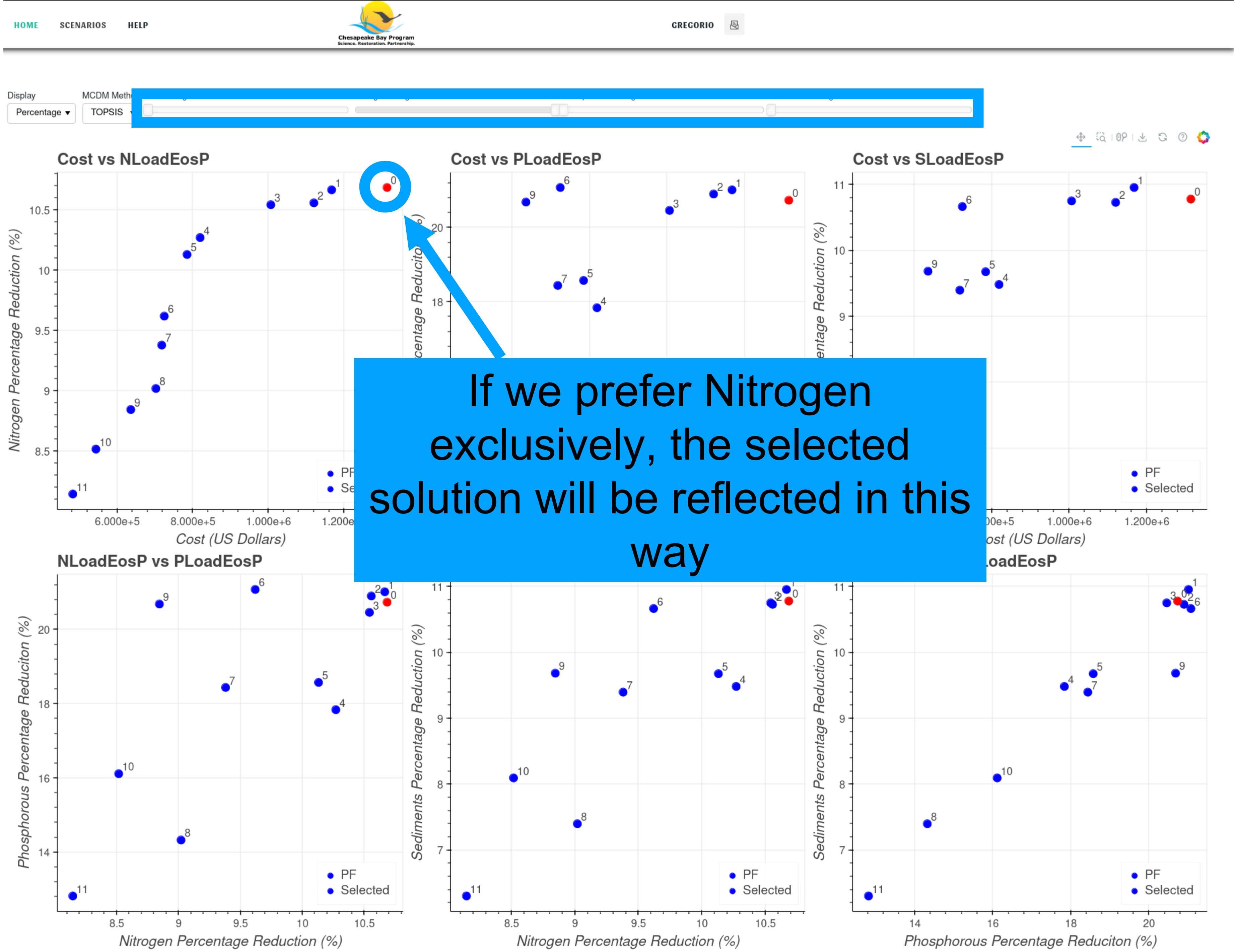
HELP
Chesapeake Bay Program
Science. Restoration. Partnership.
GREGORIO
Display
Percentage
MCDM Method
TOPSIS
Cost Weight: 0.48
Nitrogen Weight: 0.50
Phosphorous Weight: 0.50
Sediments Weight: 0.50
Cost vs NLoadEosP
Cost vs PLoadEosP
Cost vs SLoadEosP
NLoadEosP vs PLoadEosP
NLoadEosP vs SLoadEosP
PLoadEosP vs SLoadEosP
Nitrogen Percentage Reduction (%)
Phosphorous Percentage Reduciton (%)
Sediments Percentage Reduction (%)
Cost (US Dollars)
PF
Selected
Produces a ranking preference, where 0 is the preferred solution.



If we assign the lowest preference to COST, then the TOPSIS prefers the reduction of Loads.



If we increase the preference for COST, then the prefer solution becomes the cheapest scenario.


HOME
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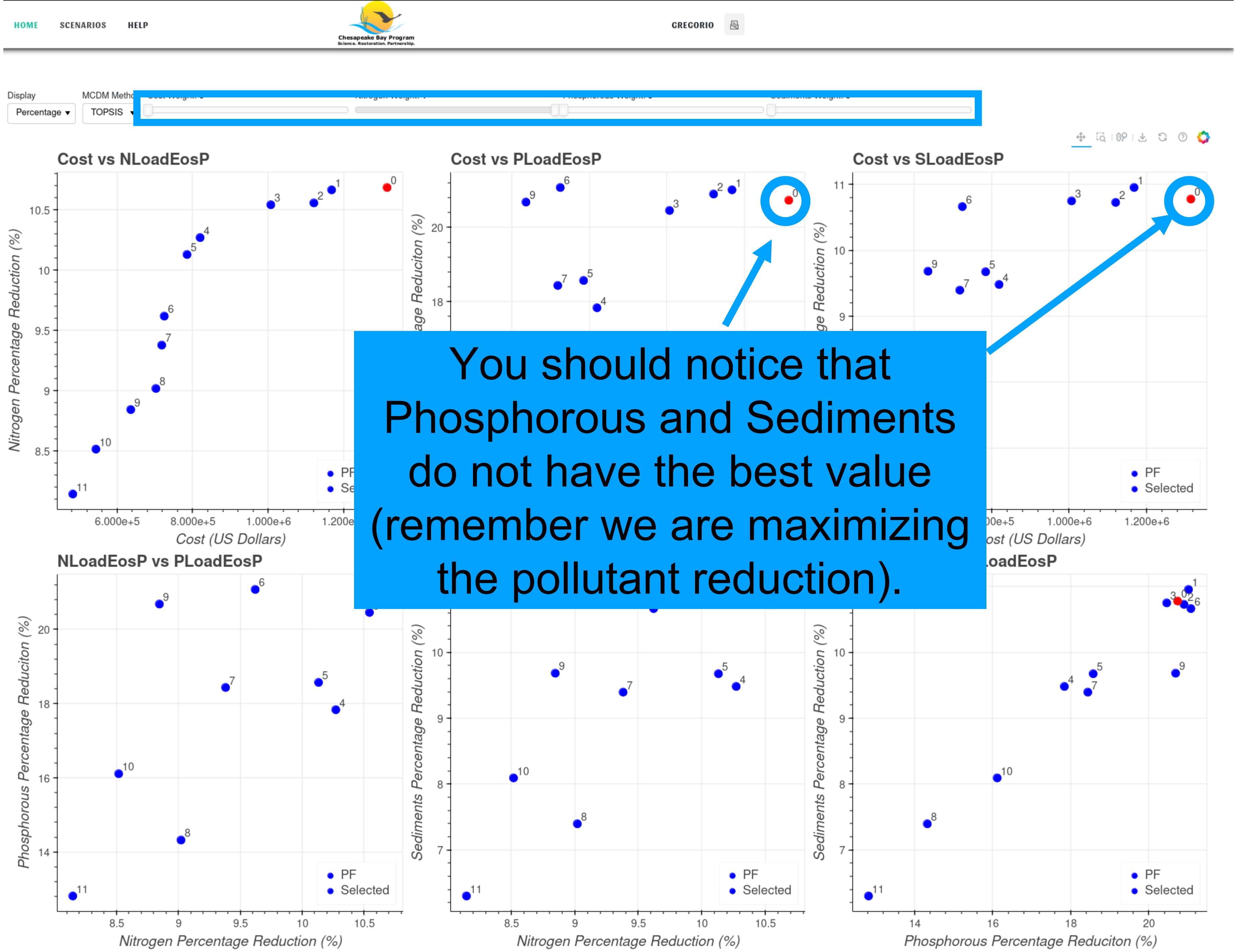
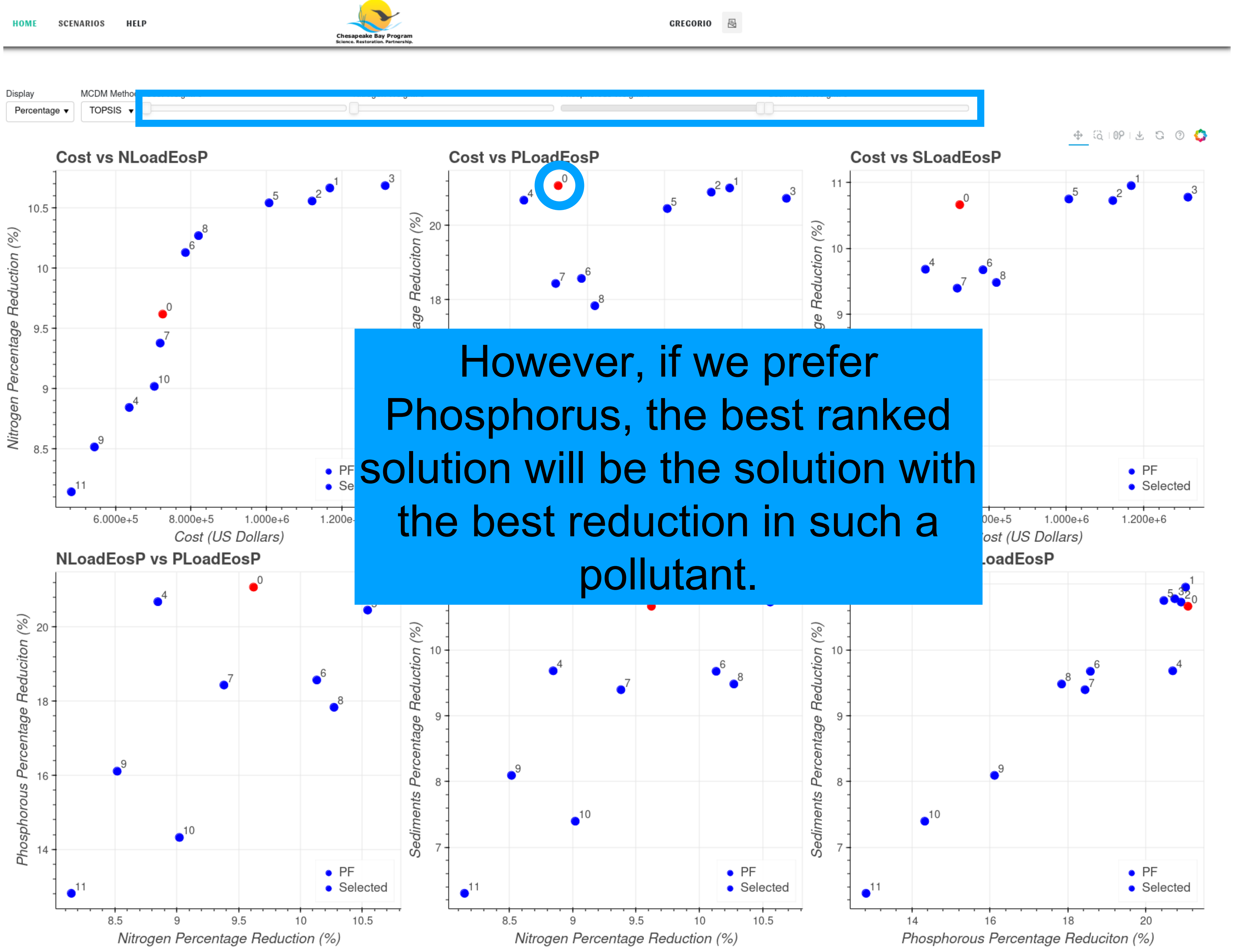
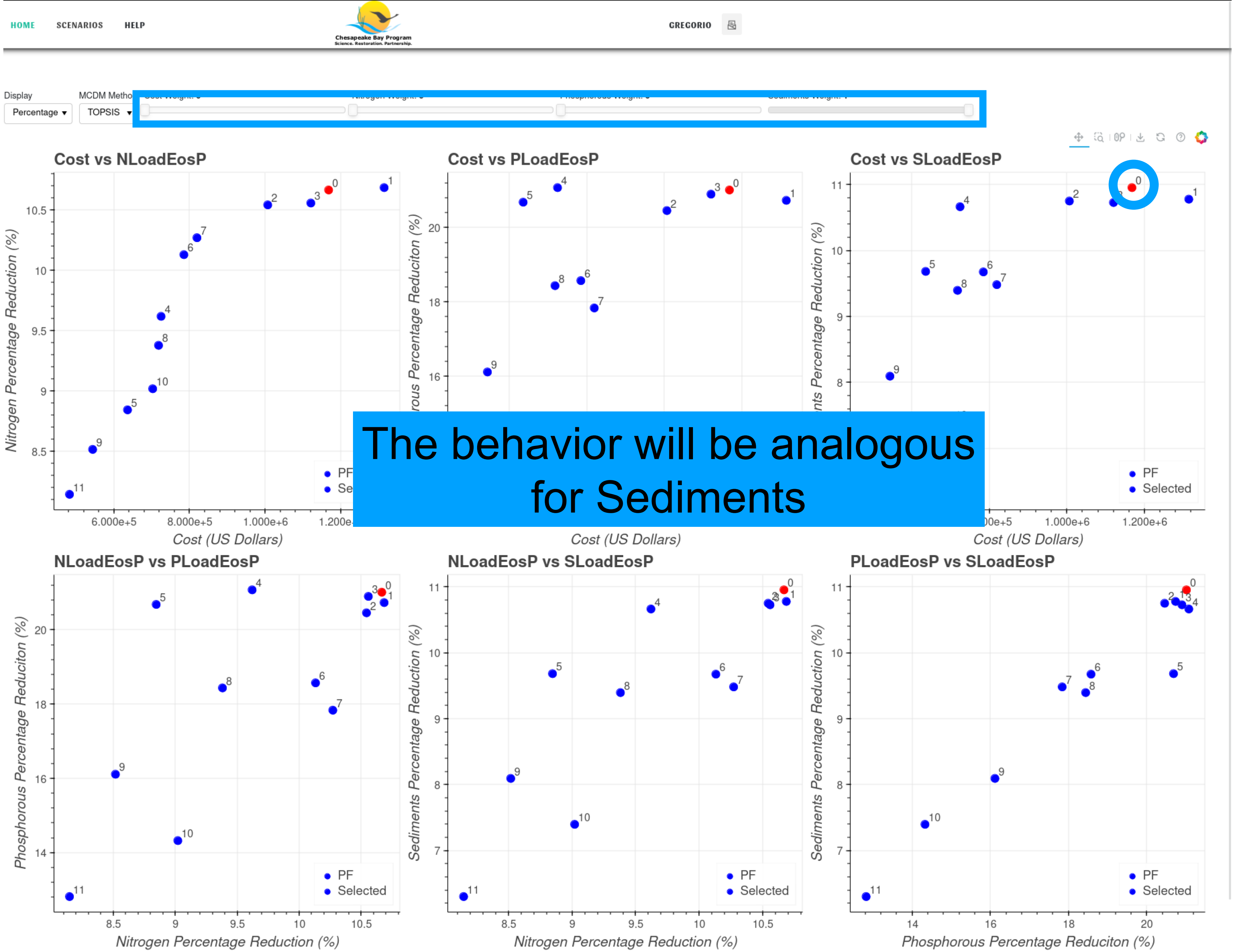
GREGORIO
Display
Percentage
MCDM Meth
TOPSIS
Cost vs NLoadEosP
Cost vs PLoadEosP
Cost vs SLoadEosP
NLoadEosP vs PLoadEosP
Nitrogen Percentage Reduction (%)
Cost (US Dollars)
Phosphorous Percentage Reduciton (%)
Sediments Percentage Reduction (%)
Nitrogen Percentage Reduction (%)
Phosphorous Percentage Reduciton (%)
PF
Selected
If we prefer Nitrogen exclusively, the selected solution will be reflected in this way



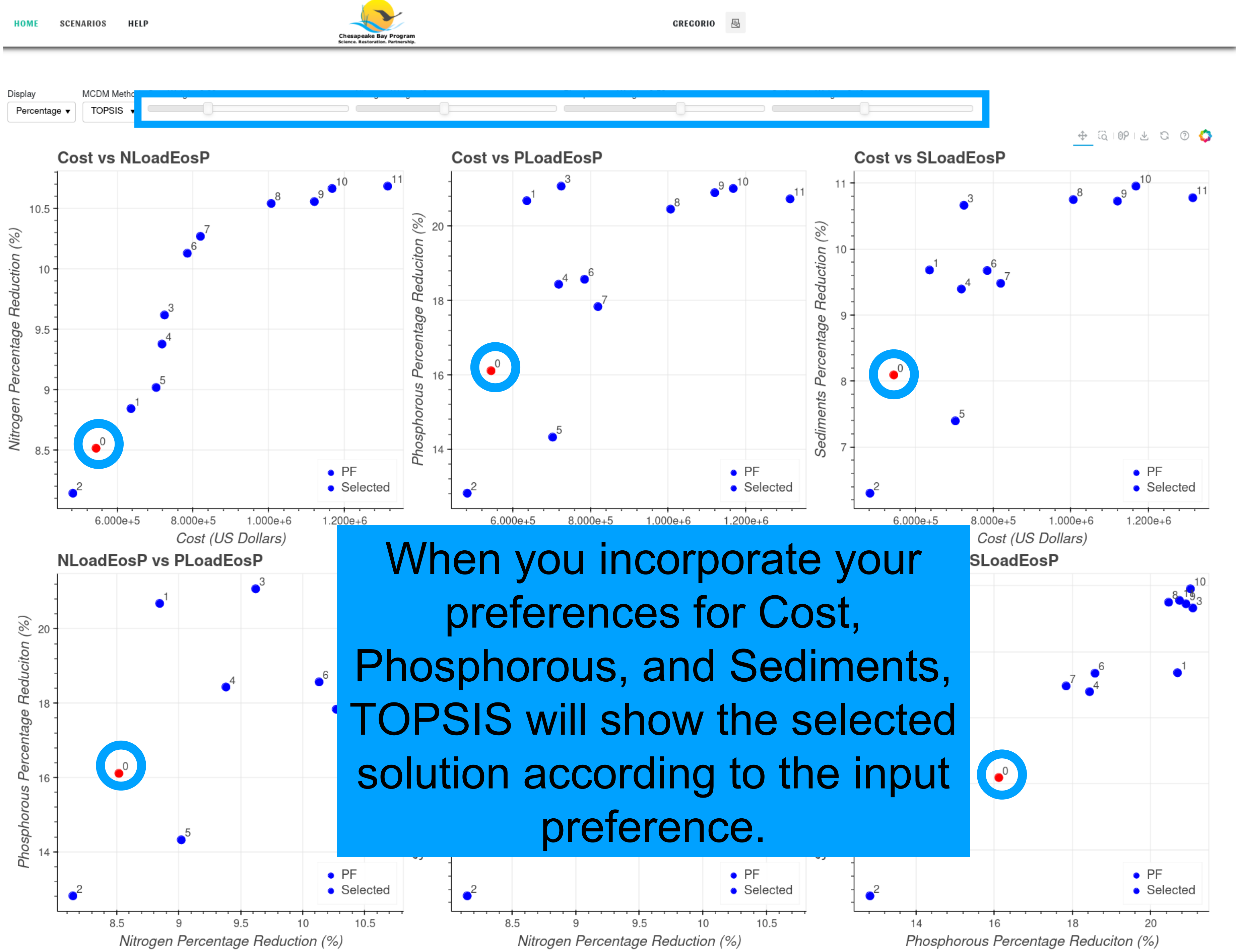
You should notice that Phosphorous and Sediments do not have the best value (remember we are maximizing the pollutant reduction).



However, if we prefer Phosphorus, the best ranked solution will be the solution with the best reduction in such a pollutant.



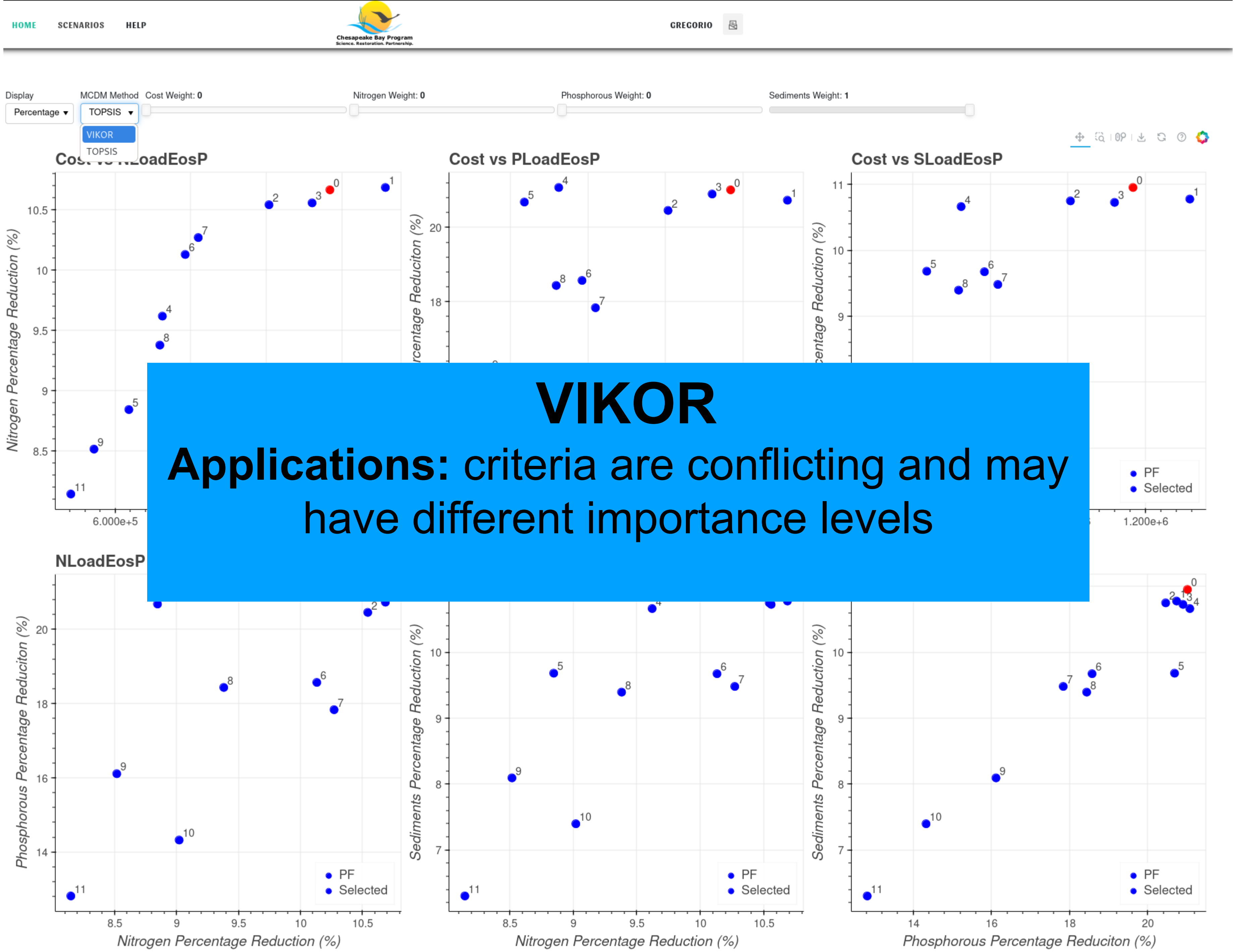
The behavior will be analogous for Sediments

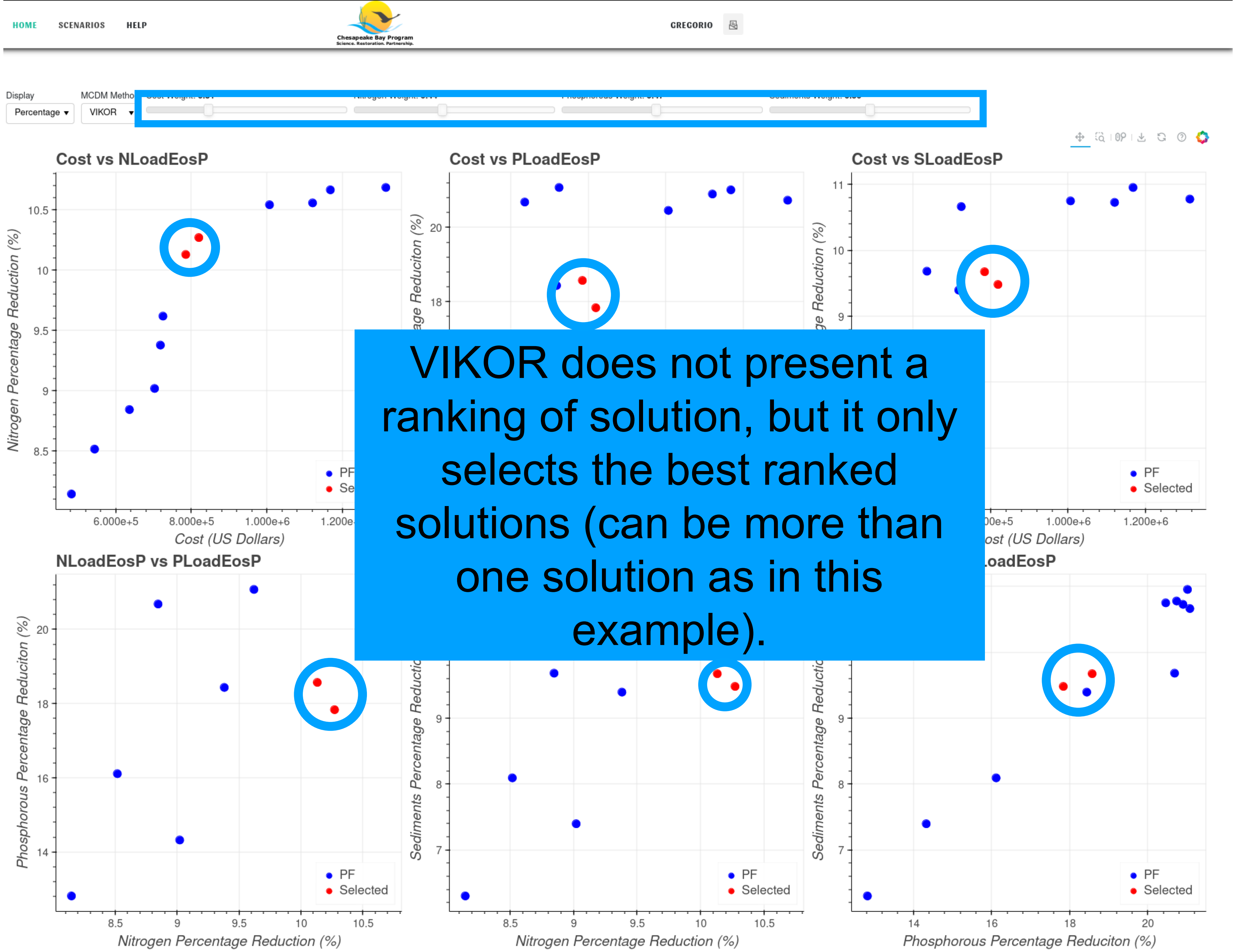


When you incorporate your preferences for Cost, Phosphorous, and Sediments, TOPSIS will show the selected solution according to the input preference.

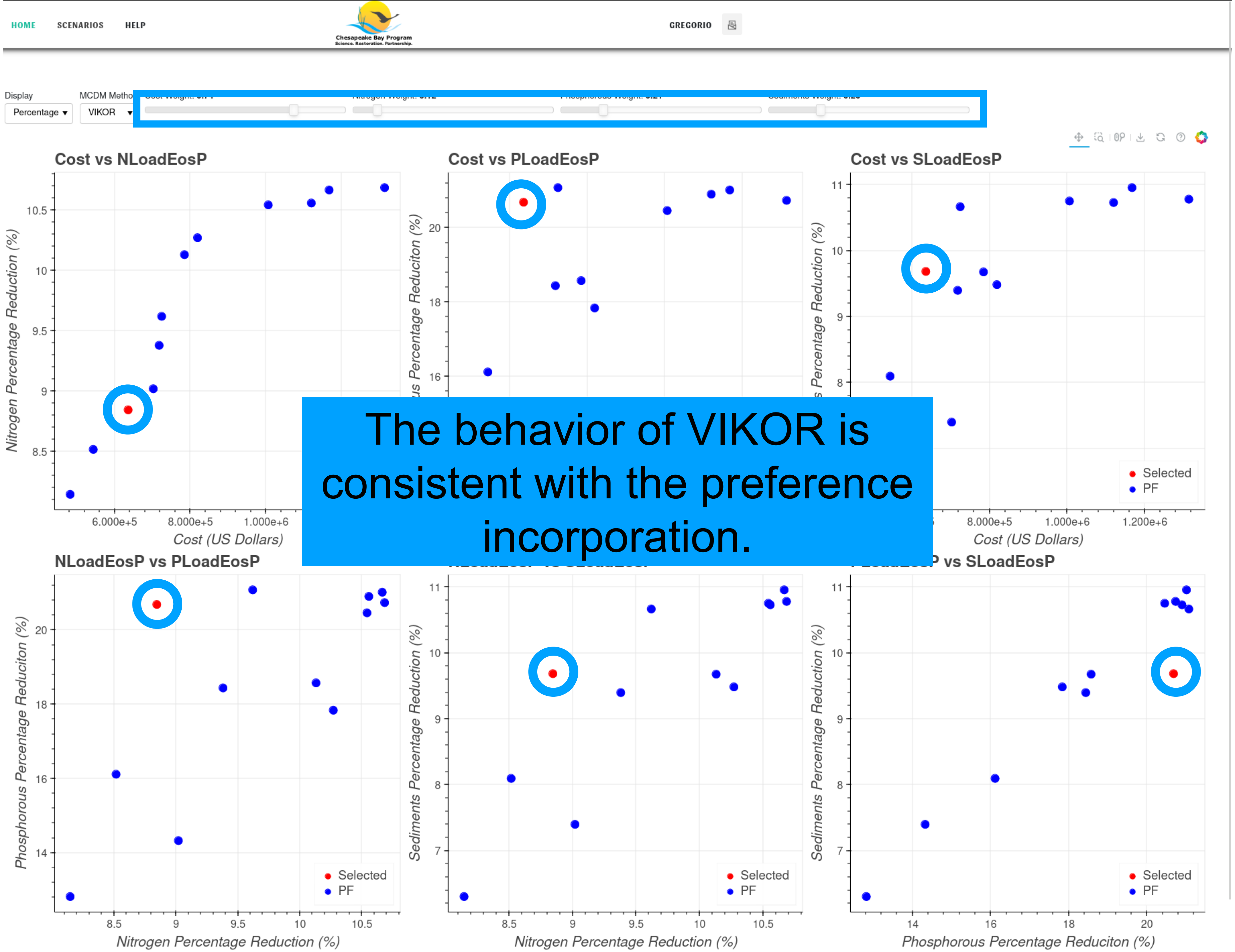
VIKOR

Applications: criteria are conflicting and may have different importance levels

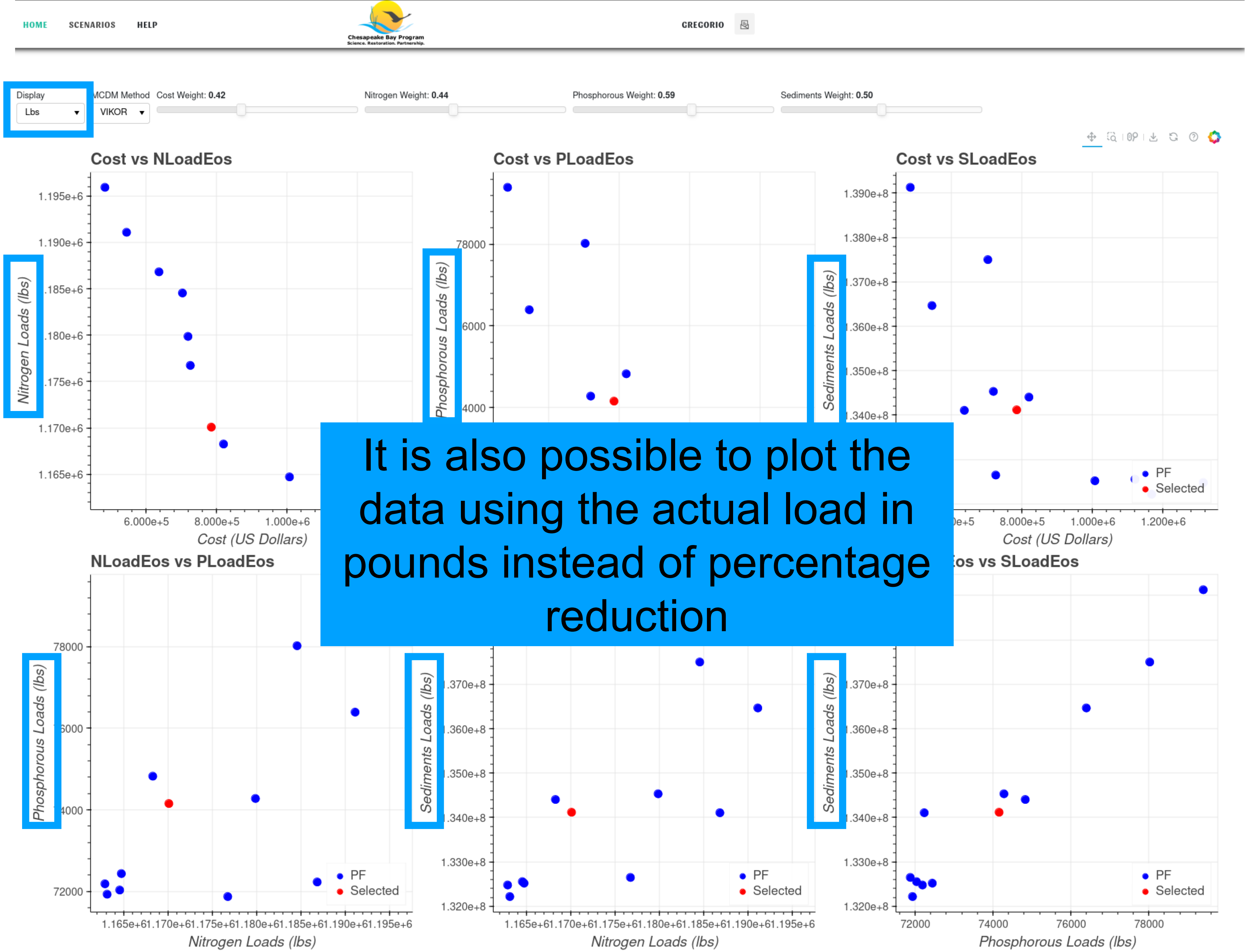




VIKOR does not present a ranking of solution, but it only selects the best ranked solutions (can be more than one solution as in this example).



The behavior of VIKOR is consistent with the preference incorporation.


HOME
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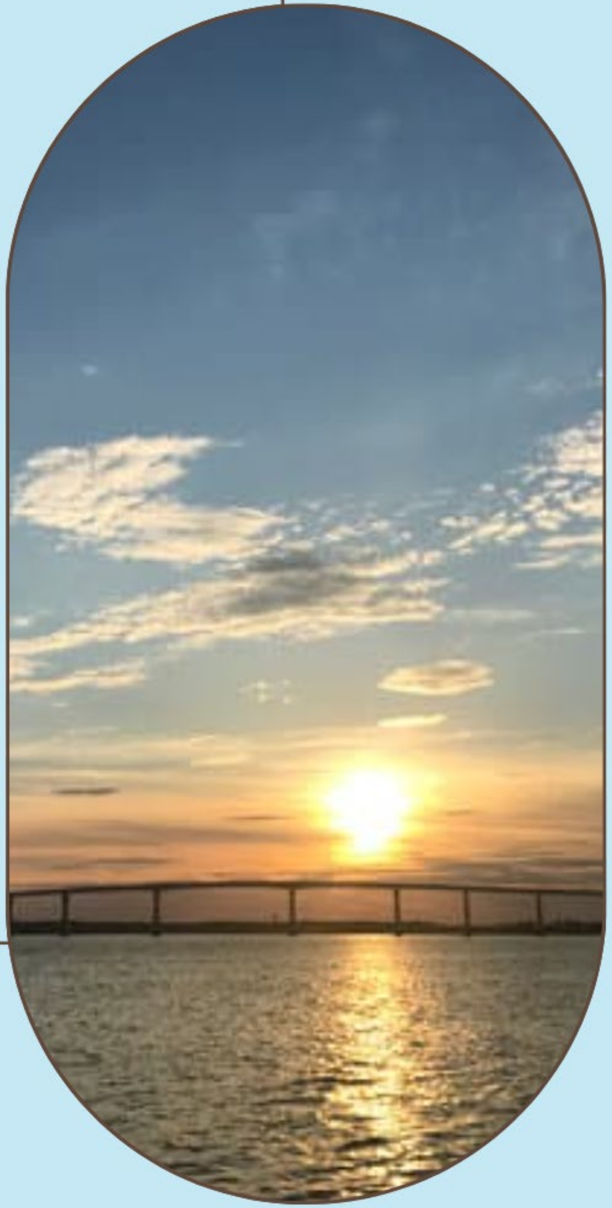
HELP
Chesapeake Bay Program
Science. Restoration. Partnership.
GREGORIO
Display
Lbs
MCDM Method
VIKOR
Cost Weight: 0.42
Nitrogen Weight: 0.44
Phosphorous Weight: 0.59
Sediments Weight: 0.50
Cost vs NLoadEos
Cost vs PLoadEos
Cost vs SLoadEos
NLoadEos vs PLoadEos
Nitrogen Loads (lbs)
Phosphorous Loads (lbs)
Sediments Loads (lbs)
Cost (US Dollars)
PF
Selected
It is also possible to plot the data using the actual load in pounds instead of percentage reduction

NEXT STEP

- Using artificial intelligence to enhance optimization
- 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.

Features:

* Interactive show of the framework capabilities

Benefits:

* Enhanced decision-making
* Foster community collaborations

MICHIGAN STATE
UNIVERSITY

Computational Optimization and Innovation

Thank you

C-ECO

Computational Ecohydrology