ABSTRACT

MCELVENNY, ANNE ELIZABETH. Optimizing National Implementation of Phosphorus Removal Technologies. (Under the direction of Dr. Jordan Kern).

Phosphorus is a critical nutrient for plant growth and food security, yet its nonrenewable nature, limited production rate, and growing demand present significant challenges. Phosphorus nutrient pollution also poses a substantial threat to water quality across the United States. Municipal Wastewater Treatment Plants (WWTPs) offer a unique opportunity for addressing both issues through phosphorus removal, with the potential for recovery and reuse.

Given a hypothetical federal budget, such as the 2021 Bipartisan Infrastructure Bill, we explore how mathematical optimization models can be used to identify the most effective allocation of resources based on various priorities. Our study compares optimal investment decisions under eight different scenarios in which the objective function and constraints were altered to incorporate consideration of local water quality impairment levels and P limitation status, as well as economies of scale We found that there is a potential for this type of optimization to be used in decision making when presented with multiple priorities and a limited investment budget. Our results showed impairment status to be less impactful on investment decisions than expected, while P limitation had a large impact on the selection of sites when considered without impairment. We expected economies of scale to have a strong influence on the size of the plants chosen for investment, but this did not have a significant impact on the mean size of selected WWTPs. Our analysis framework and findings aim to inform policy and investment decisions in phosphorus management, with the potential for enhancing sustainability and preserving water quality.

Optimizing National Implementation of Phosphorus Removal Technologies

by
Anne Elizabeth McElvenny

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Natural Resources

Raleigh, North Carolina

2024

APPROVED BY:

_____	_____
Dr. Jordan Kern Committee Chair	Dr. Justin Baker
_____	_____
Dr. Paul Westerhoff	Dr. Rachel Cook

DEDICATION

Nothing of significance was ever accomplished alone. Thank you to everyone that has helped me along the way, especially Dr. Jordan Kern. None of this would have been possible without the support of my friends, family, and Wolfpack community.

BIOGRAPHY

Anne Elizabeth McElvenny moved several times at young age but now calls the mountains of Travelers Rest, South Carolina her family's home. At 16 years old, Anne left home for the South Carolina Governor's School for Science and Mathematics in Hartsville, South Carolina to pursue a rigorous two-year residential high school program and jumpstart her career. She received a full merit scholarship to attend Clemson University and there she earned her Bachelor of Science in Environmental and Natural Resources in 2022.

Anne continued her education North Carolina State University in Raleigh, North Carolina for her Master of Science in Natural Resources with a concentration in Policy and Administration. After graduation, Anne has a position with the U.S. Environmental Protection Agency through Oak Ridge Associated Universities contracts as a Research Communications Specialist in Research Triangle Park, North Carolina.

ACKNOWLEDGMENTS

This project was conducted through the Science and Technologies for Phosphorus Sustainability Center (STEPS), which is a convergence research community funded by the National Science Foundation to address the complex challenges in phosphorus sustainability. A special thank you to my committee members, Dr. Jordan Kern, Dr. Justin Baker, Dr. Paul Westerhoff, and Dr. Rachel Cook. I'd also like to thank Dr. Daniel Obenour for his expertise on Wastewater Treatment and Dr. Natalie Nelson for her guidance. Finally, I'd like to thank Minhazul Islam for his contribution of data and his continued collaboration.

TABLE OF CONTENTS

LIST OF TABLES

.

LIST OF FIGURES

CHAPTER 1

Introduction

Phosphorus, Potassium, and Nitrogen are the three main nutrients crucial for plant growth. While nitrogen-based fertilizers, such as ammonia, can be manufactured via the Haber-Bosch process, phosphorus can only be produced from mined rock. Phosphorus demand is increasing, yet there is a limit on the amount and the rate of phosphorus that can be produced (Cooper et al 2011). With no via substitute in food production (Cordell, Rosmarin et al 2011), managing non-renewable phosphorus resources is key to maintaining and improving food security in the future (Cordell, Drangert et al 2009).

At the same time, excessive contributions of phosphorus from both point sources such as effluent from wastewater treatment plants (WWTPs) and confined animal feeding operations, and nonpoint sources such as crop-based agricultural runoff, pose significant threats to water quality and aquatic ecosystems. Forty-six percent of the United States' (US) river and stream miles are rated poor because of excess levels of phosphorus (USEPA, 2017). In some systems, excess phosphorus nutrients can cause algal blooms, setting off a sequence of detrimental effects on aquatic ecosystems (Harper, 1992). When the algal blooms are consumed by detritivores, the dissolved oxygen levels in the water become extremely limited, leading to massive fish kills and shifts in species composition across many trophic levels (Correll, 1998). These harmful algal blooms can pose public health risks (e.g. exposure to cyanotoxins and water quality) and broader economic risks to humans including decreased recreation and tourism, water treatment costs, and decreased property values (Dodds et al 2009).

While nonpoint sources are the dominant source of nutrients in watersheds, point sources still contribute >50% of the P and N reaching rivers from urbanized areas (Newman, 1995), and

the local impacts of point sources may exceed those of a nonpoint source scattered throughout a watershed (Puckett, 1995). Moreover, there can be challenges in identifying, quantifying, and addressing the main source of nonpoint source pollution in watersheds (Carpenter et al., 1998). Municipal wastewater is a well-understood point source of phosphorus in natural water bodies. Total P concentration in municipal wastewater influent is typically between 6 and 8 mg/L (Parsons & Smith, 2008). The availability and precision of data on phosphorus concentrations in treated wastewater effluent varies by state and watershed. However, compared to nonpoint source pollution, WWTPs represent a comparatively rich dataset for establishing new mechanistic modeling frameworks and evaluating potential mitigation measures, and thus are the focus of this thesis.

Increasing freshwater demand and water quality regulations have long served as the primary driver for nutrient removal and recovery efforts at WWTPs. (Liu et al., 2008) (USEPA 2004) (Carpenter et al., 1998). Regulations are implemented at WWTPs through a Total Maximum Daily Load (TMDL) based on a National Pollutant Discharge Elimination System (NPDES) permit if discharging into waters of the United States. These permits specify acceptable level of pollutant allowed in a discharge, determined by each state. In the case of phosphorus, the value of recovered phosphorus as a fertilizer (di-ammonium phosphate has increased in price by more than 200% since 2019) may become an additional incentive to reducing the stress on the phosphorus cycle from cradle to grave.

The 2021 United States Infrastructure Investment and Job Act provided $55 billion for water infrastructure and $21 billion in environmental protection, not including the $8.3 billion set aside for developing Western water infrastructure (Zhang 2022). A portion of these funds could

be used to improve water quality and reduce P in waterways with removal and recovery technologies at WWTPs.

There are multiple possible objectives when allocating federal funding for water quality improvement, such as: maximizing P removal, maximizing P recovery and reuse, maximizing ecosystem restoration and water quality improvement, as well as considerations for equity and environmental justice (for example, distributing funds equally or addressing longstanding differences in pollution burden) (Ogneva-Himmelberger et al., 2015).

Prioritizing one objective over another could lead to different decisions about where investment in P removal takes place. For example, maximizing the total amount of P removed while constrained by a fixed budget could concentrate investment in P removal at the very largest WWTPs. If we account for "economies of scale" (decreased per-unit costs of treatment as a function of plant size), recovery of phosphorus from small sewage plants in rural and semi-urban areas may not be economically optimal due to lower amounts of recoverable P and increased investment costs due to a loss of scale (Sarvajayakesavalu et al 2018).

Given limited federal funds for P removal and multiple possible objectives driving investment, an outstanding question is how sensitive are optimal investment decisions to alternative formulations of the optimization problem? Formal multi-objective optimization has been used widely in water resource management research (Zheng et al. 2016), including design of best management practices (BMPs) of phosphorus in specific watersheds (Ji, 2022). However, previous research has not addressed phosphorus technology implementation on a national scale. In this paper, we develop an initial analytical framework for identifying globally optimal phosphorus removal siting strategies across the US, constrained by a set investment budget. This research represents one of the first attempts to evaluate this problem within the context of actual federal

funding opportunities, and we hope the results to inform future model development and eventually, policy and investment decisions.

Methods

Overview

Figure 1 shows an overview of the analytical approach taken in this study. We created a simple mathematical optimization (integer program) to determine the optimal investment in P removal technologies at the 200 largest WWTPs in the US. With a set budget of $38 billion, only a limited number of plants can be chosen for investment. We evaluate 8 different technology options; each option has a different capital and operating cost and P removal efficiency. The model determines what combination of investments will maximize our objective function, and we define 8 different versions of the model that prioritize different objectives and have different constraints. Results show how alternative formulations of the objective function alter where P removal investment occurs across the US.

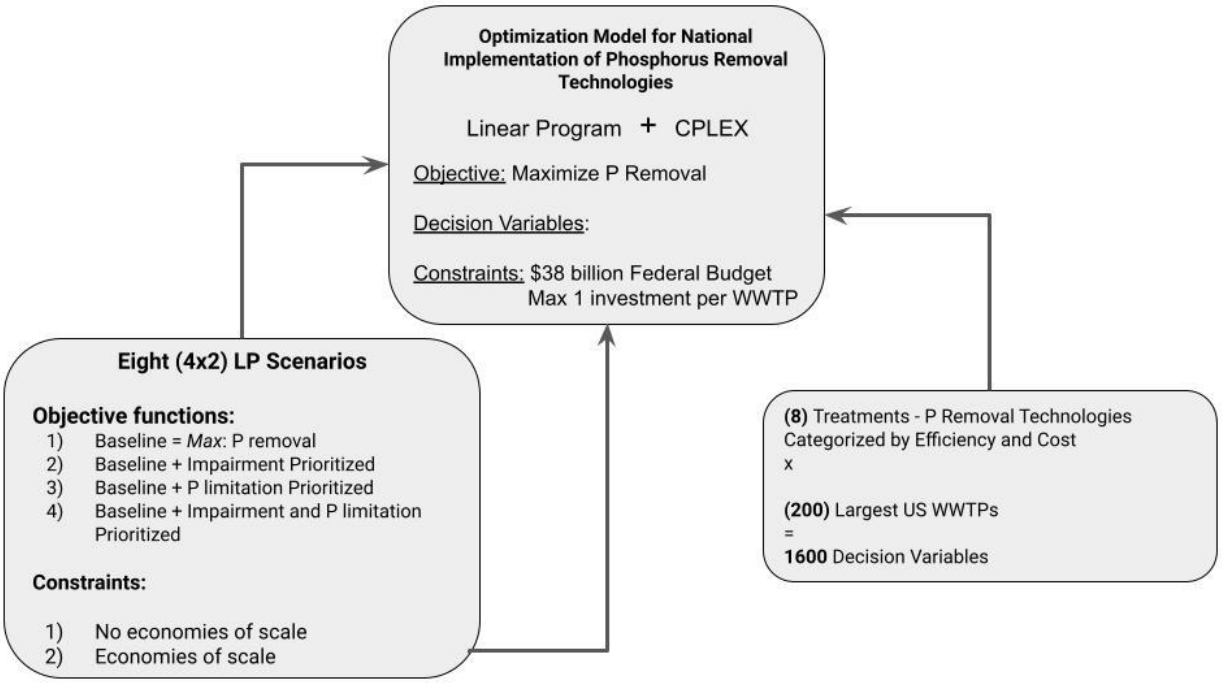


Figure 1 – Overall methodological approach to model with eight scenarios.

Data

WWTP database

We limited the scope of our study to the 200 largest WWTPs by million gallons per day (MGD) in the continental United States based on data collected from the 2012 Clean Watersheds Needs Survey conducted by the US Environmental Protection Agency. The 200 largest WWTPs were selected because these 200 WWTPs account for more than 50% of total recoverable P in WWTPs in the US (Islam, 2023). We assume that there are no current P removal technologies at these sites and that current P influent concentrations are uniform across all WWTPs at 8 mgP/L.

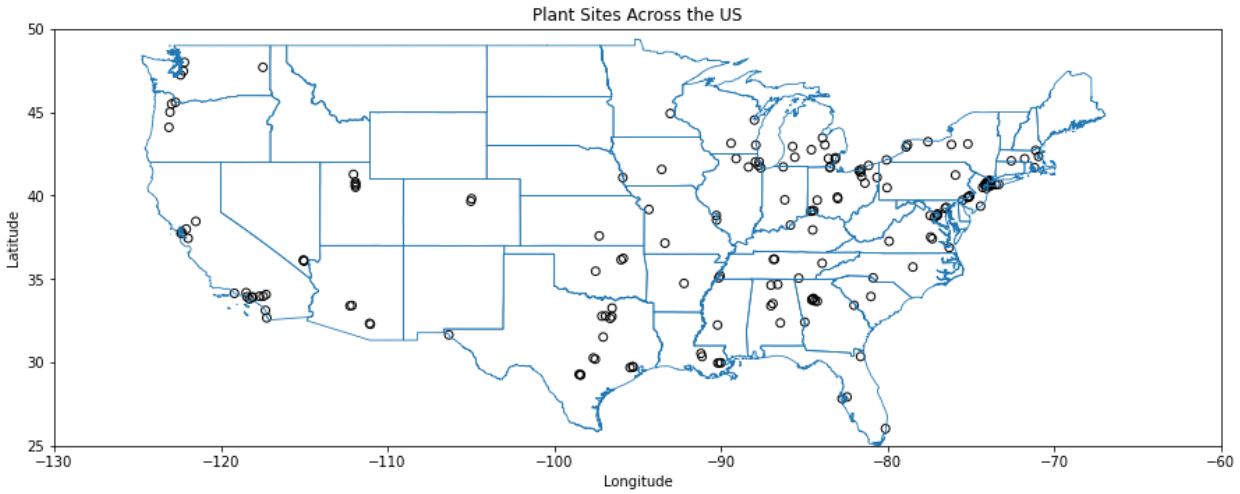


Figure 2 – Map of 200 largest US WWTPs used in this analysis.

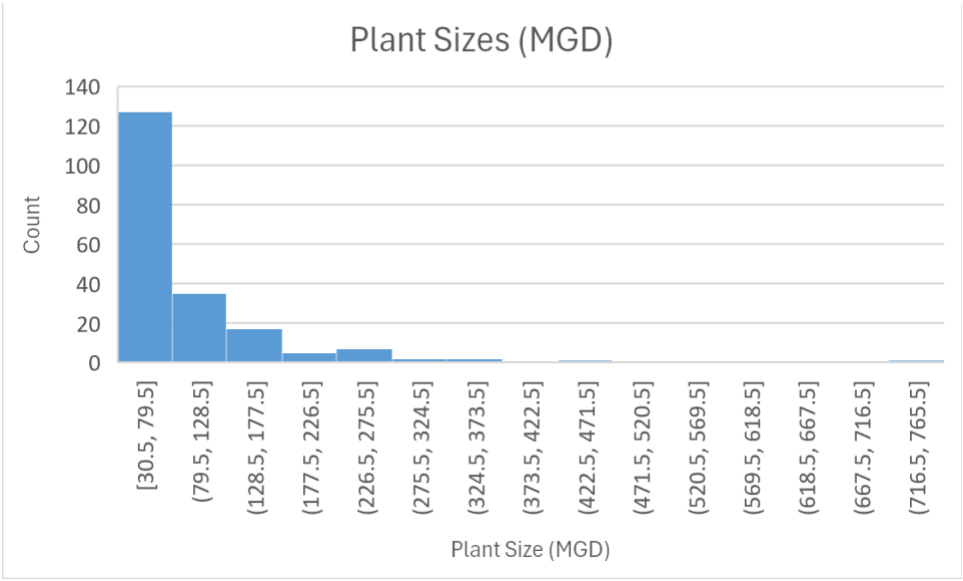


Figure 3 – Histogram showing the distribution of the size of WWTPs used in study. Not shown are the two largest WWTPs (with sizes of 1200 MGD and 4453MGD).

Categorization of Treatment Technologies

We created eight categories of treatment technologies with data from an EPA report on 62 different municipal treatment technologies and the associated costs for nutrient pollution control.

For each P removal technology, the report provided estimated capital costs in dollars per gallons per day ($/gpd), annual O&M costs ($/gpd/year), and resulting, post-treatment total phosphorus effluent concentrations (mg/L). Figure 4 below demonstrates the relationship between the capital cost and effluent concentration.

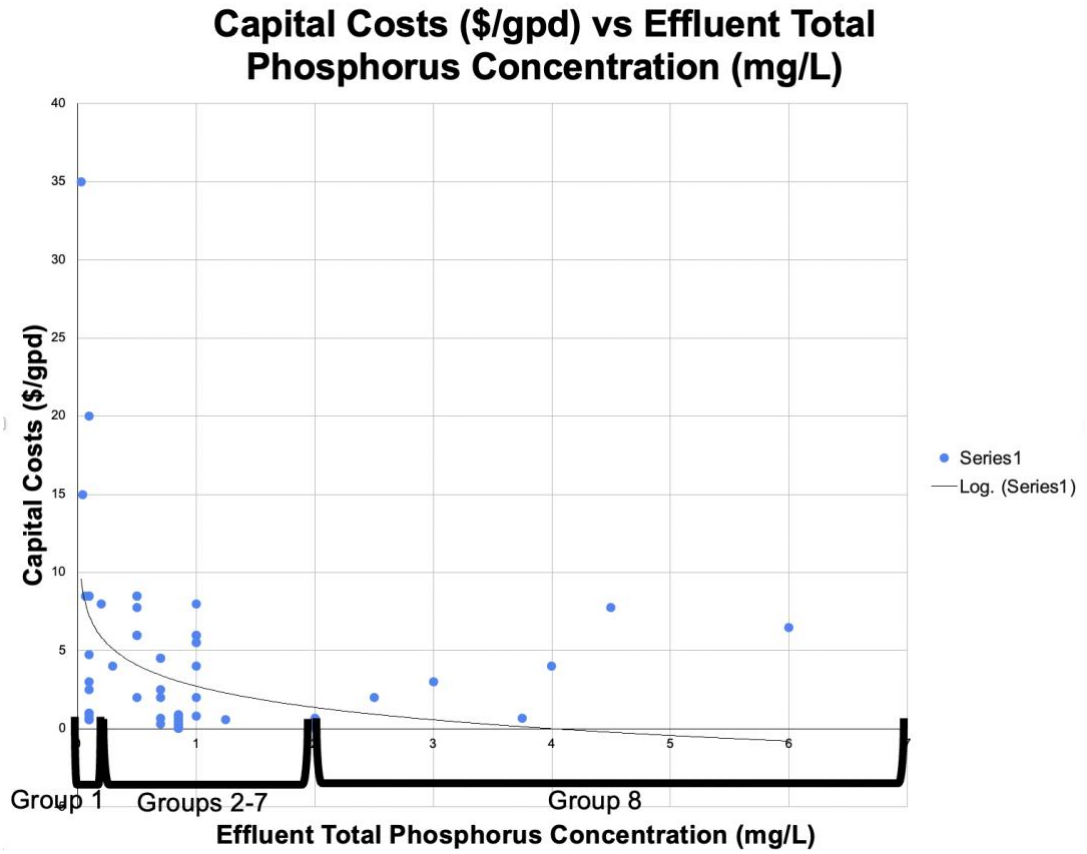


Figure 4 – Plot of capital cost ($/gpd) versus effluent total P concentration (mg/L) used to determine the treatment categories.

We then grouped the 62 technologies into eight clusters, or representative technologies, to simplify the model's decision-making. Groups were formed based on each technology's ability to remove phosphorus relative to the cost.

First, we fit logarithmic function to the 2-dimentionsal data shown in Figure 4. We observed that the function poorly characterized technologies with extreme values of P removal, so we created two separate regions of the plot to represent these end member technology groups: Group 1, which includes technologies with very low P effluent concentrations but very high capital costs; and Group 8, which has very high P effluent concentrations and high capital costs.

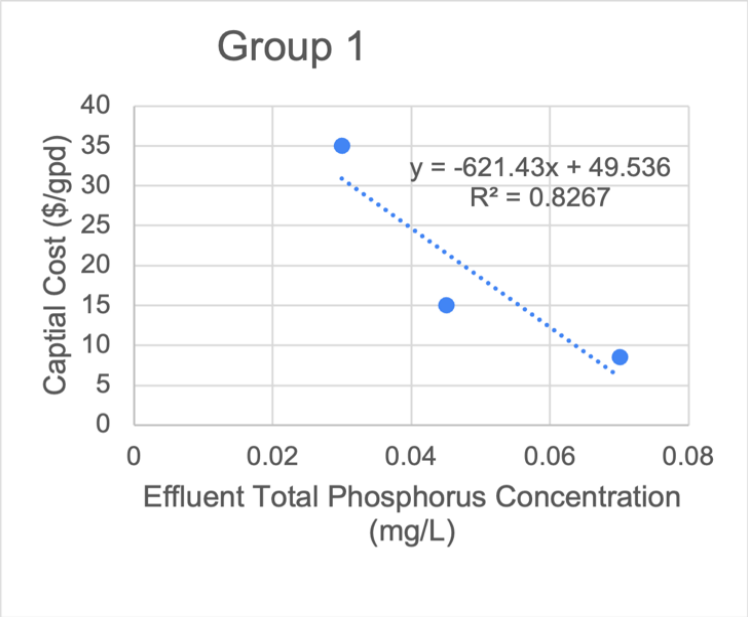


Figure 5 – Plot of effluent concentration versus capital cost for Group 1 treatment options.

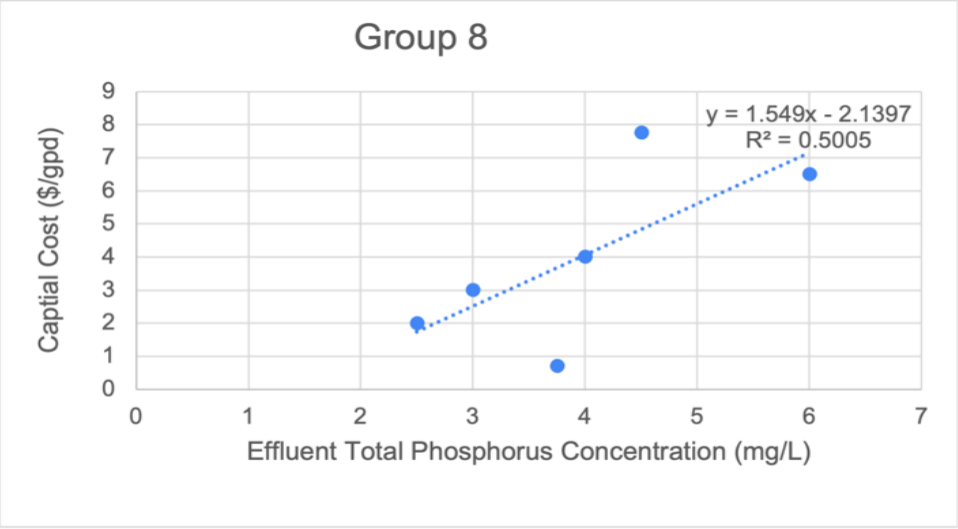


Figure 6 – Plot of effluent concentration versus capital cost for Group 8 treatment options.

A simple linear regression was fitted for the points in Group 1 and Group 8.

- Group 1: y (capital cost in $) = -621.43x (effluent concentration in mg/L) + 49.536
- Group 8: y (capital cost in $) = 1.549x (effluent concentration in mg/L) – 2.1397

Then, we determined the y-value associated with the median x-value within each group and took that cost/efficacy pair as our representative Group 1 and Group 8 technologies.

A similar process was used to create 6 other representative technologies. In between Group 1 and Group 8, the EPA data was fit to a logarithmic function:

Groups 2-7: y (capital cost in $) = -1.198ln(x) (effluent concentration in mg/L) + 2.2186

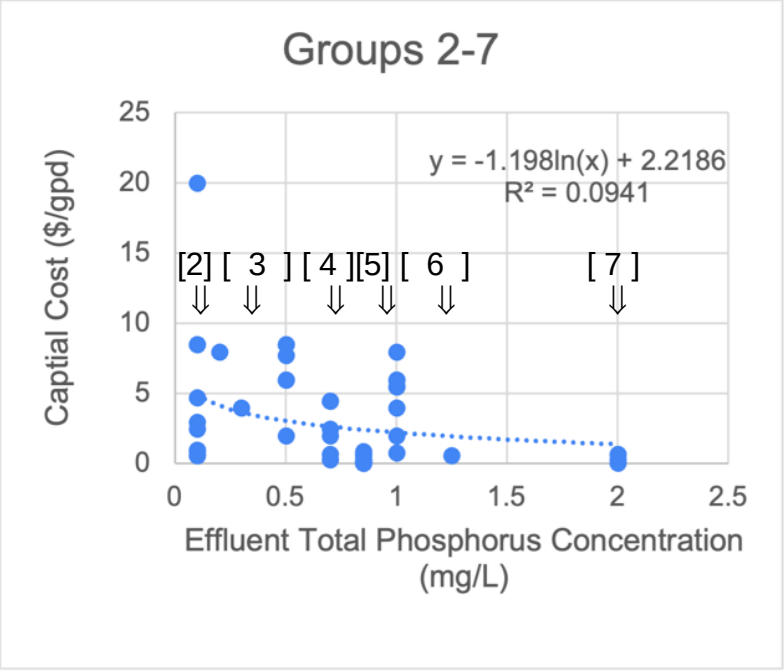


Figure 7 – Groups 2-7 shown on plot of capital cost versus effluent total concentration.

We determined the y-values associated with 6 different x-values (phosphorus effluent concentrations of <0.1, 0.2-0.5, 0.7, 0.85, 1-1.25, and 2 mg/L, respectively), and took those combinations of P removal efficiency and capital costs as our remaining, 6 representative technologies.

Table 1 – Effluent and Cost Values Used in Model for 8 Treatment Technology Options.

Treatment Technology Category	Average P Effluent (mg/L)	Median P Effluent (mg/L)	Capital Costs ($/MGD)	O & M Costs ($/MGD/year)
Option 1	0.048	0.045	49.54	0.8
Option 2	0.1	0.1	4.977	0.3
Option 3	0.438	0.5	3.209	0.3
Option 4	0.7	0.7	2.646	0.2
Option 5	0.85	0.85	2.413	0.2
Option 6	1.028	1	2.219	0.2
Option 7	2	2	1.388	0.2
Option 8	3.958	3.875	3.863	0.3

The actual P removed by implementing a technology at a given WWTP is determined by subtracting the after-treatment effluent concentration from the assumed 8 mgP/L influent value, and then multiplying by the volume of water treated (WWTP size).

$a_{t,p}$ = [influent (8 mgP/L) – effluent (mgP/L)] x Volume Treated (L/year)

For example, for a WWTP with treatment volume of 1200 MGD (1,658,010,361,392 Liters per year), which invests in P removal Option 2 (achieving an after treatment effluent concentration of 0.1mgP/L), the total P removed per year would be:

(8 mgP/L - 0.1mgP/L) x 1,658,010,361,392L = 13,098,281 kgP/year

Optimization Model - Baseline Scenario

Our integer programming (IP) model was designed with 1600 total binary decision variables, comprising 200 location choices and 8 treatment technology options.

We first defined a baseline scenario in which the LP maximizes P removal across all 200 WWTPs subject to a budgetary constraint, and then we defined 7 alternative scenarios that have altered formulations (objective functions and constraints). In the baseline scenario, the LP is constrained by a $38 billion limit on capital investment, which comes from the IRA funds (Infrastructure Investment and Jobs Act, Pub. L. No. 117-58 (2021). In addition, we imposed constraints on investment at each WWTP, such that the model could not choose to invest in more than one technology per plant.

Only one treatment per plant

$$\sum_{t=1}^{8} d_{p,t} = 1 \ \forall \, p$$

Budget Constraint

$$\sum_{t=1}^{8}\sum_{p=1}^{200} d_{p,t} * \ c_t * s_p \leq \ 38{,}000{,}000{,}000$$

Where,

t is treatment option in set {1…8}

p is WWTP in set of 200 largest {1…200}

$d_{p,t}$ = binary decision variable [0,1] denoting investment in treatment option t and plant p

c_t = capital cost of treatment option t in $/MGD

s_p = size of WWTP in MGD

The baseline scenario includes the following objective function of maximizing total P removal:

$$\max \quad \sum_{t=1}^{8}\sum_{p=1}^{200} [d_{p,t} \cdot \ a_{t,p}]$$

Where,

$a_{t,p}$ = P removed from plant p using treatment Option t in

Impairment (I_p)

In the second version of the model, we added to the objective function some consideration of the need to invest in P removal in water quality impaired watersheds. We identified the sub-

watersheds of each WWTP and gave them a numerical level of impairment (I_p), allowing the model to prioritize investment at WWTPs in more impaired watersheds.

The level of impairment was collected from the U.S. EPA's "How's My Waterway?" (USEPA, 2023), which reports the percentage of the total area assessed that is reported as impaired under section 303 of the Clean Water Act for multiple criteria. This includes a value for the percentage of assessed areas deemed impaired for Nitrogen and/or Phosphorus by watershed, with 0 being no assessed areas reported as impaired and 100 being 100% of areas assessed were reported as impaired. Scenario 2 adds the prioritization of watersheds with higher levels of nutrient impairment (I_p) to the objective function, as follows:

$$\max \quad \sum_{t=1}^{8} \sum_{p=1}^{200} [d_{p,t} \cdot a_{t,p}] * I_p$$

Where,

I_p = the impairment level, from 0 to 1, measuring the proportion of assessed waters deemed impaired

For a given WWTP (p), if the associated I_p value is small, this change in the objective function incentivizes investment at other WWTPs with greater impairment levels. However, if the associated I_p is large, this change in the objective function incentivizes investment in that plant.

P limitation (L_p)

As many coastal and estuarine ecosystems are limited by Nitrogen and would receive fewer benefits from P removal, third version of the model was created to prioritize investment at WWTPs in P-limited watersheds by introducing a term L_p, whose values range from 0 to 1.

First we determined which WWTPs were coastal and estuarine ecosystems via conductivity levels. Conductivity data were obtained from EPA's Freshwater Explorer using nearby monitoring stations' range of specific conductivity (μS/cm). We excluded the stations measuring water directly from the WWTP, which are often much higher and do not represent the overall waterbody's status.

Any WWTP with a direct ocean discharge or conductivity values above 33,000 μS/cm was assumed to have a P limitation value of $L_p = 0$, providing no direct water quality incentive for investment (Howarth & Marino, 2006).

Conductivity values between 5,000 and 33,000 μS/cm were deemed estuarine or coastal ecosystems, meaning less valuable P removal in the model, but more ecologically valuable than removing P from saltwater. For every other location, conductivity values ranged from 11 μS/cm to 5000 μS/cm. For any site with a conductivity value less than 33,000 μS/cm, an equation was applied to determine the L_p value so that as the salinity/conductivity increased, the value would reflect this change.

$$L_p = 1 - \frac{k_p}{33000\ \mu S/cm}$$

Where,

k_p = conductivity value

Version 3 of the model directly includes prioritizing watersheds that are P limited (L_p values close to 1).

$$\max \quad \sum_{t=1}^{8}\sum_{p=1}^{200}[d_{p,t} \cdot \ a_{t,p}] * L_p$$

Where,

L_p is a proxy for P limitation, where 0 is ocean water (not P limited) and 1 is freshwater (P limited)

For a given WWTP (p), if the associated L_p value is small, this change in the objective function incentivizes investment at other WWTPs with greater levels of P limitation. However, if the associated L_p is large, this change in the objective function incentivizes investment in that plant.

Combined consideration of impairment and P limitation

The fourth version of the model considers the product of I_p and L_p in the objective function. By combining both, the resulting decisions should prioritize investment at WWTPs in areas that are *both* impaired and P limited. This allows the model to prioritize what watersheds are estimated to be the most in need of P removal from an ecological perspective.

$$\max \quad \sum_{t=1}^{8}\sum_{p=1}^{200}[d_{p,t} \cdot \ a_{t,p}] * I_p * L_p$$

Economies of Scale

In this study, the sizes of the selected WWTP were vastly different, ranging from only 30.5 MGD to 4453 MGD. Hernández-Chover et al. 2018 suggests that the presence of scale economies in this sector has a significant influence on efficiency of the wastewater treatment process, and thus the treatment costs. We assumed that for WWTPs, as the size of a plant increases, a cost advantage is gained when implementing a given P removal technology.

Specifically, we applied a cost multiplier parameter to the capital costs of each treatment technology, where the cost multiplier reflects the size of the plant where the investment is being made. We fitted a line from the smallest WWTP at 30.5 MGD to the largest WWTP at 4453 MGD, with values ranging from 1.05 and 0.95 on the y-axis. The largest plant was assigned a cost multiplier of 0.95 (a 5% reduction in capital cost for any treatment acquired) and the smallest plant was assigned a cost multiplier of 1.05 (a 5% increase). Plants in between these sizes were assigned a cost multiplier based on their proximity in size to the largest and smallest plants. Most plants saw cost increases, with the cost decreases going to a few, very large plants (Figure 8).

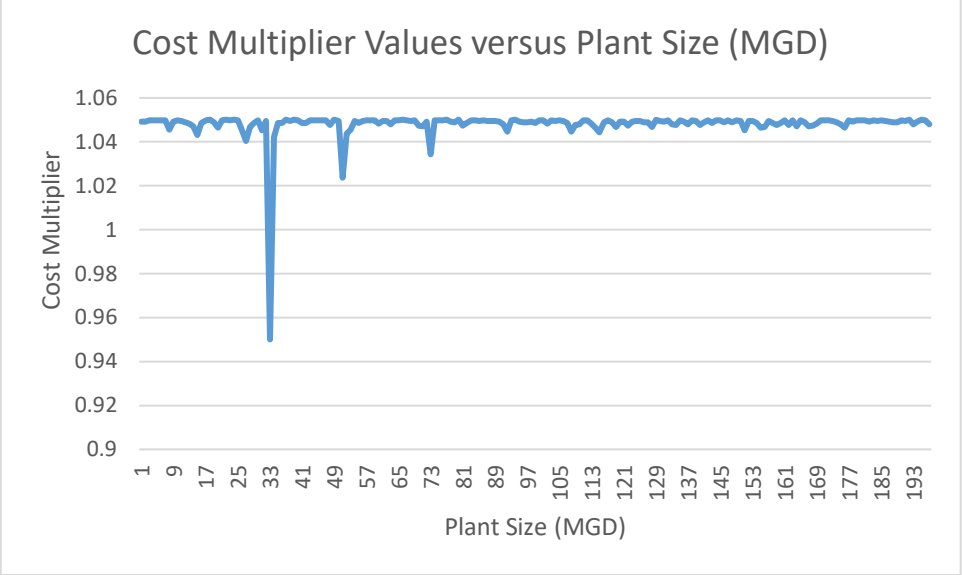


Figure 8 – Plot of cost multiplier values versus plant size (MGD).

We then created 4 additional version of the model (5-8). These have the same objective function values as versions 1-4, with an altered budget constraint that penalizes investment in P removal at smaller WWTPs.

Budget Constraint

$$\sum_{t=1}^{8}\sum_{p=1}^{200} d_{p,t} * c_t * s_p * costM_p \leq 38{,}000{,}000{,}000$$

Where,

p is WWTP in set of 200 largest {1…200}

$d_{p,t}$ = binary decision variable [0,1] denoting investment in treatment option t and plant p

c_t = capital cost of treatment option t in $/MGD

s_p = size of WWTP in MGD

$costM_p$ = cost multiplier at plant p

CHAPTER 2

Results and Discussion

Our results evaluate how alterations to the model affect the investment decisions in each of the eight scenarios. We compared each of the eight model versions in terms of the geographic location of investment, the size of the WWTPs chosen, impairment and P limitation rating for each site chose, and treatment options preferred. By doing so, we were able to determine what alterations to the model were most impactful, as well as create a set of options for decision making based on priorities.

Spatial Distribution of P removal Investment

Figures 9-16 show the distribution of the selected sites for each scenario. Each map represents the following combinations.

Table 2 – Table describing eight scenarios and their components.

Scenario	**Components**
1	Baseline
2	Baseline + Impairment
3	Baseline + P Limitation
4	Baseline + Impairment + P Limitation
5	Baseline + Economies of Scale Constraint
6	Baseline + Impairment + Economies of Scale Constraint
7	Baseline + P Limitation + Economies of Scale Constraint
8	Baseline + Impairment + P Limitation + Economies of Scale Constraint

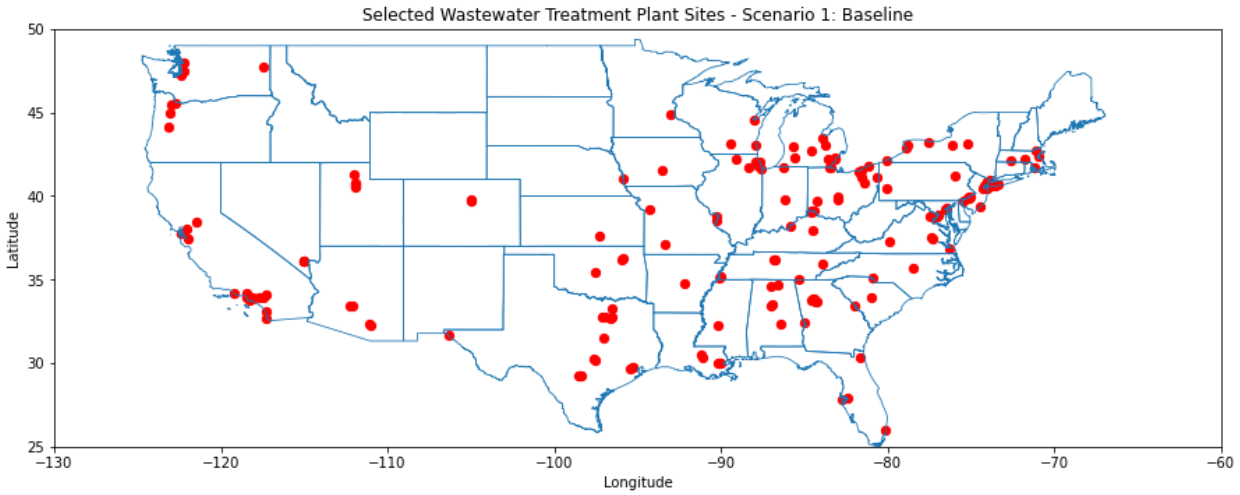


Figure 9 – Selected WWTPs for Scenario 1 on a Map of the United States

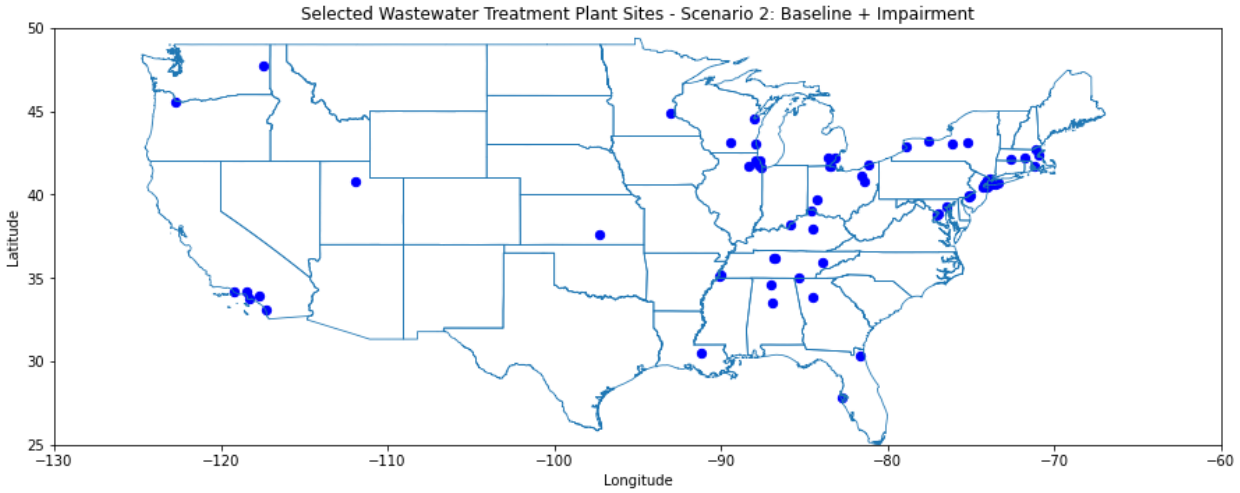


Figure 10 – Selected WWTPs for Scenario 2 on a Map of the United States.

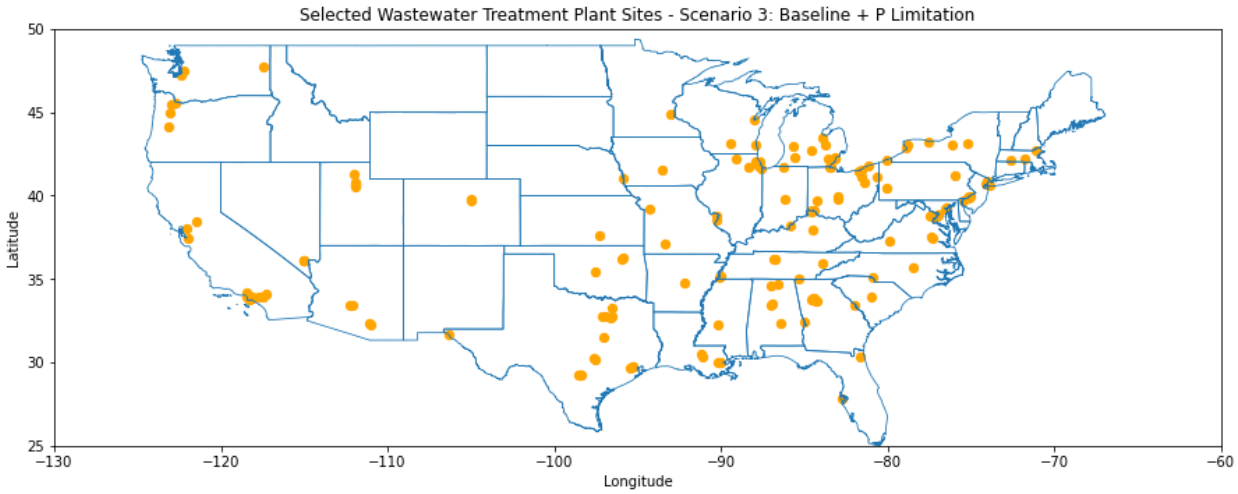


Figure 11 – Selected WWTPs for Scenario 3 on a Map of the United States.

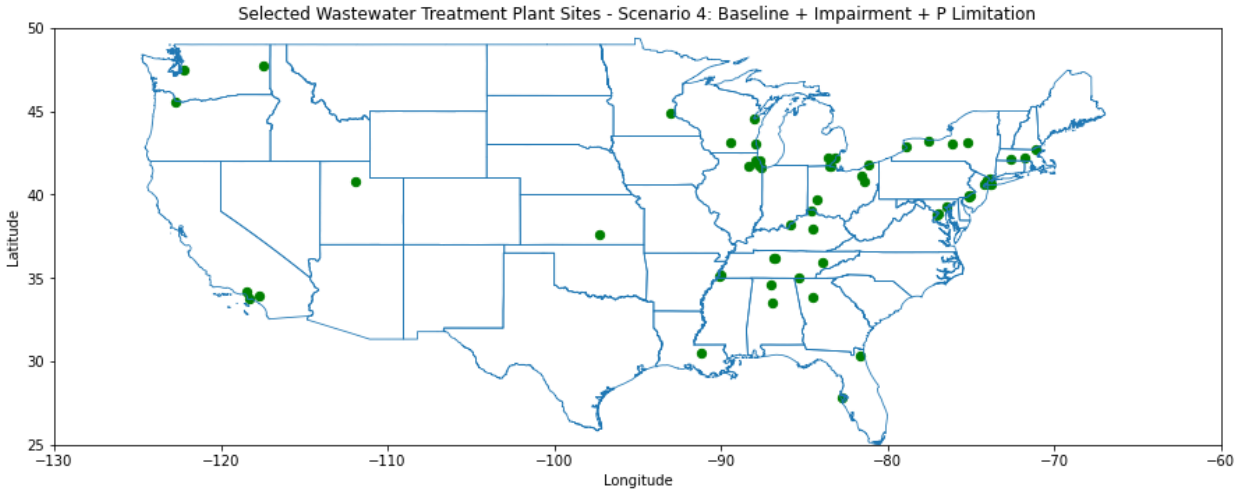


Figure 12 – Selected WWTPs for Scenario 4 on a Map of the United States.

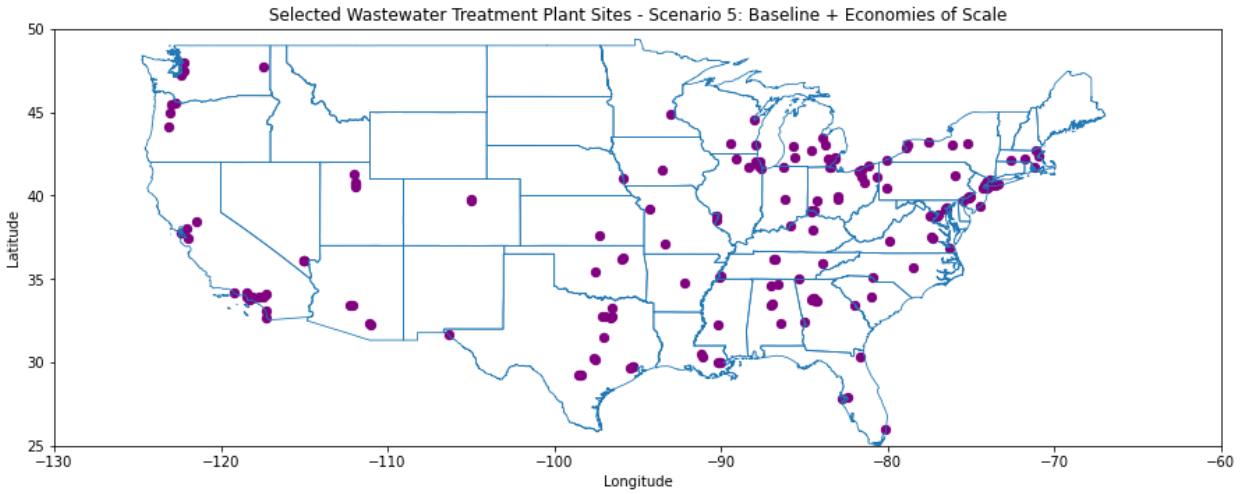


Figure 13 – Selected WWTPs for Scenario 5 on a Map of the United States.

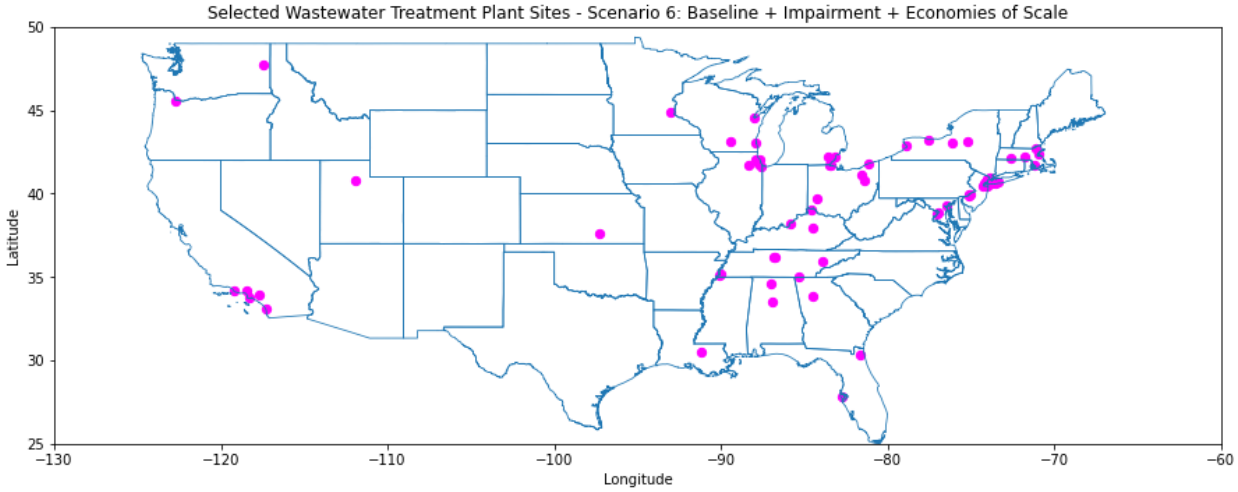


Figure 14 – Selected WWTPs for Scenario 6 on a Map of the United States.

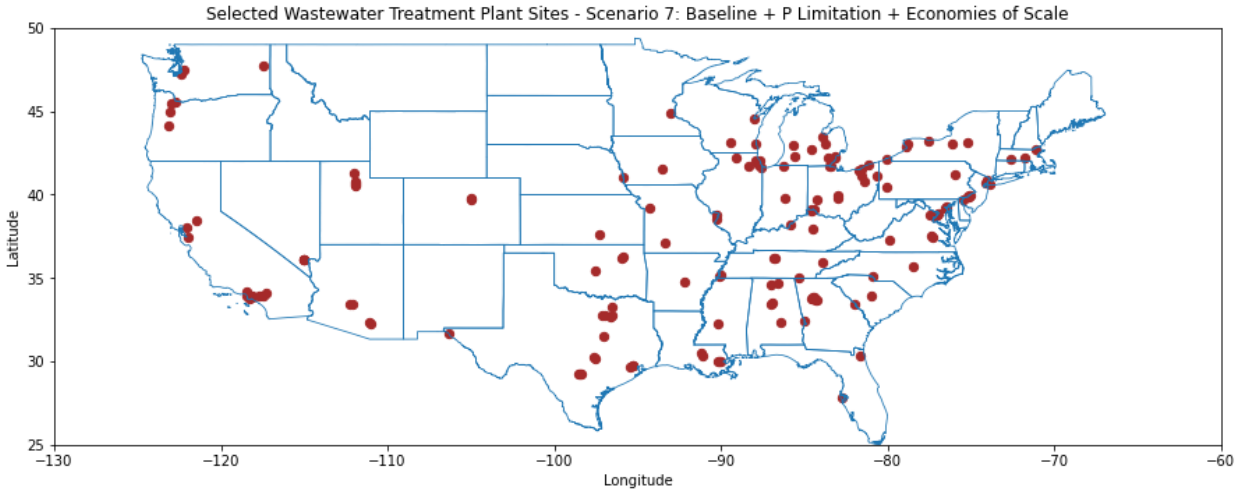


Figure 15 – Selected WWTPs for Scenario 7 on a Map of the United States.

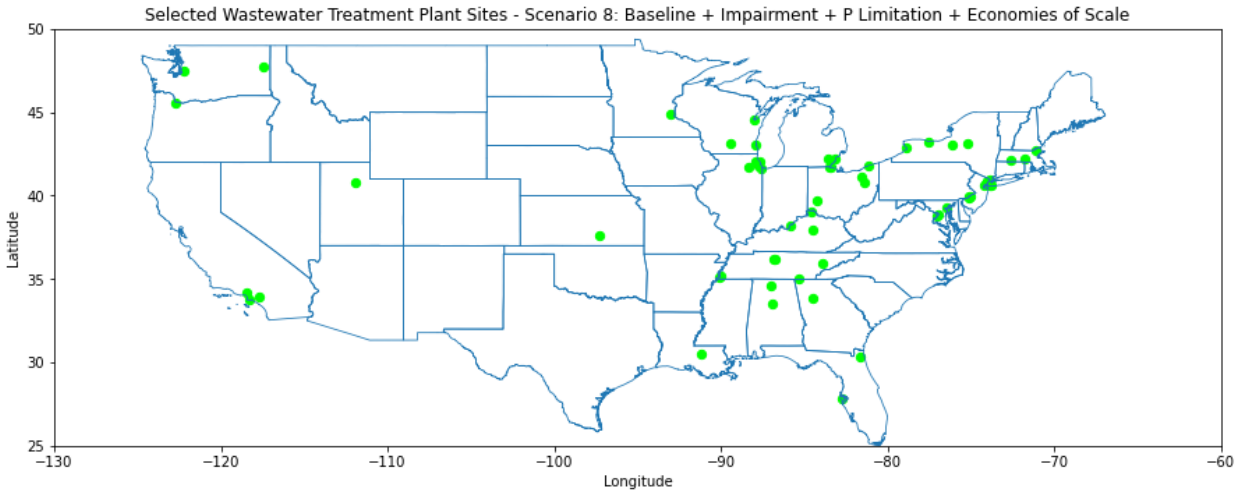
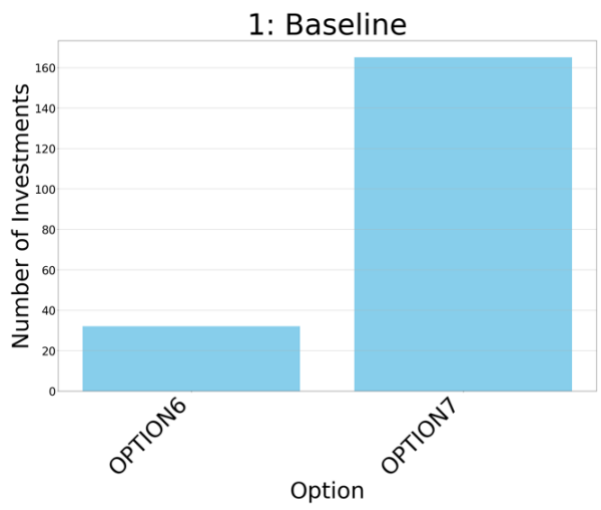
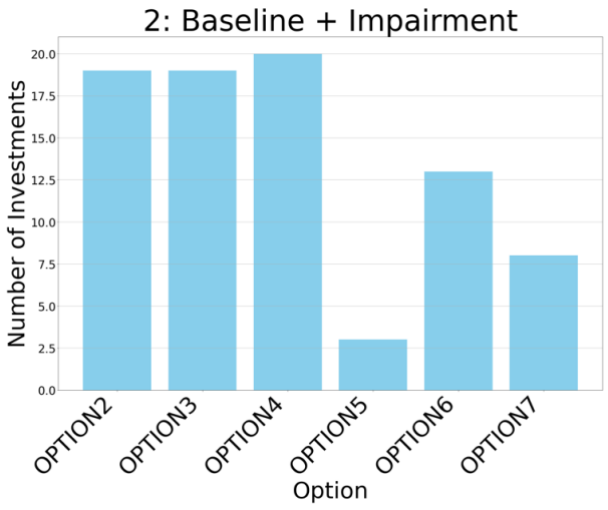


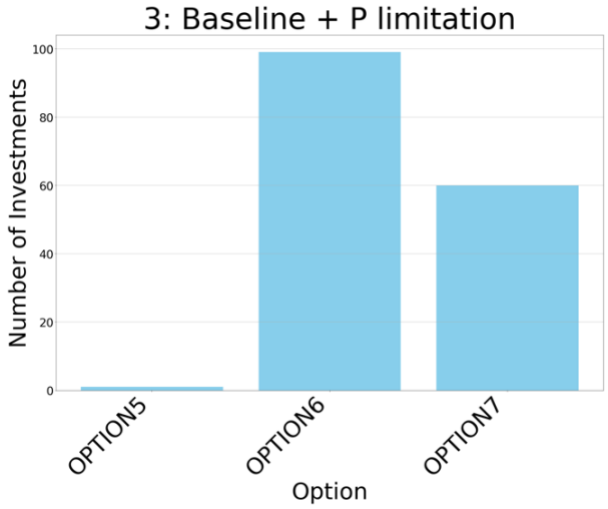
Figure 16 – Selected WWTPs for Scenario 8 on a Map of the United States.

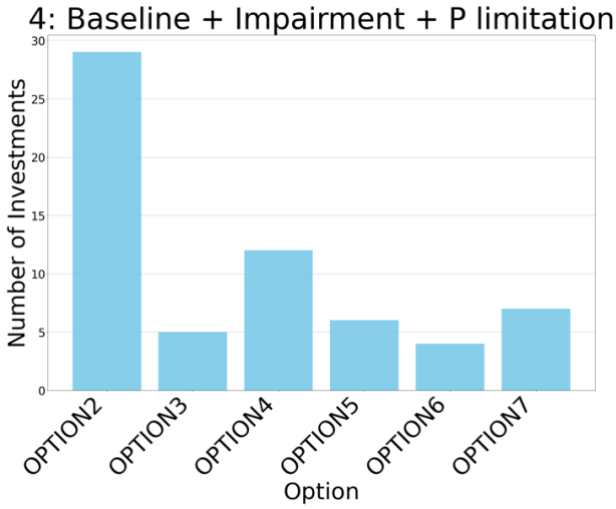
In Figures 9-16, each map shows the locations of WWTPs that were selected for investment. Each scenario alters the model, either through the objective function or an added economies of scale constraint, and causes a different group of WWTPs to be chosen for investment. The model uses the qualities of each WWTP, whether by size, impairment value (I_p), P limitation value (L_p), to determine the optimal distribution of funds. Along with seeing a slight variation in the number of markers, we also see how the geographic location of the sites changes in every scenario. There is a clear pattern where in the scenarios in which L_p (P limitation) is solely prioritized; the sites are more frequently clustered towards inland and located further away from the coast, which have generally higher salinity values and therefore lower L_p values.

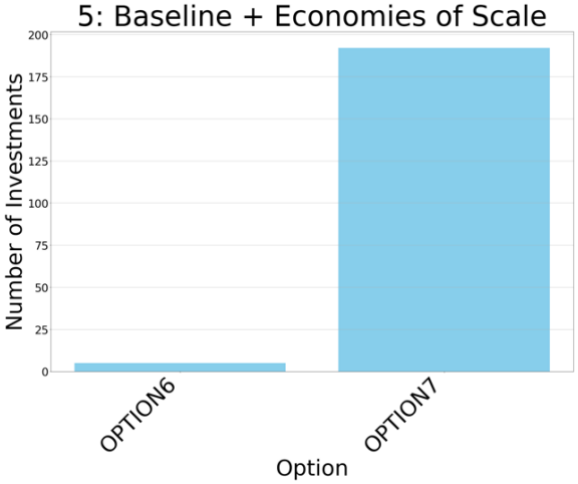
Figure 17 – Number of Investments per Option for 8 Scenarios.

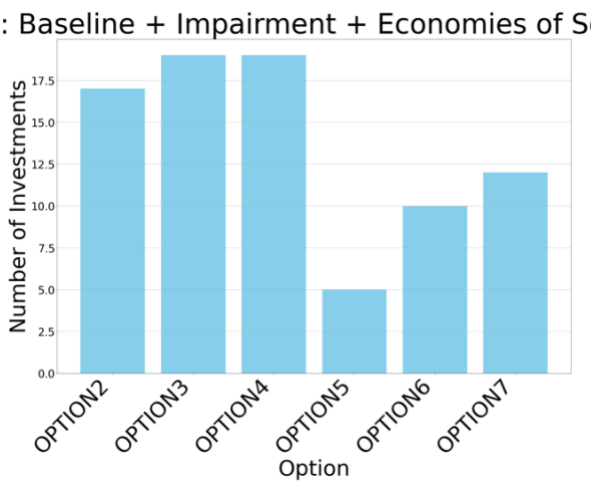

1: Baseline
Number of Investments
0
20
40
60
80
100
120
140
160
OPTION6
OPTION7
Option


2: Baseline + Impairment
Number of Investments
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
OPTION2
OPTION3
OPTION4
OPTION5
OPTION6
OPTION7
Option

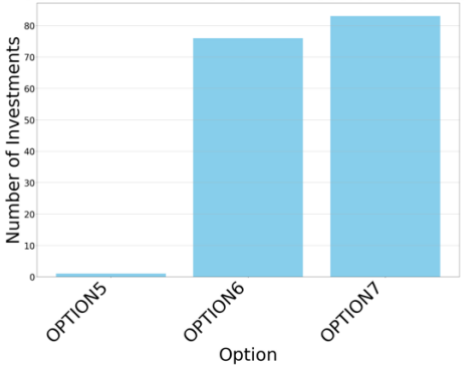

3: Baseline + P limitation
Number of Investments
0
20
40
60
80
100
OPTION5
OPTION6
OPTION7
Option


4: Baseline + Impairment + P limitation
Number of Investments
0
5
10
15
20
25
30
OPTION2
OPTION3
OPTION4
OPTION5
OPTION6
OPTION7
Option

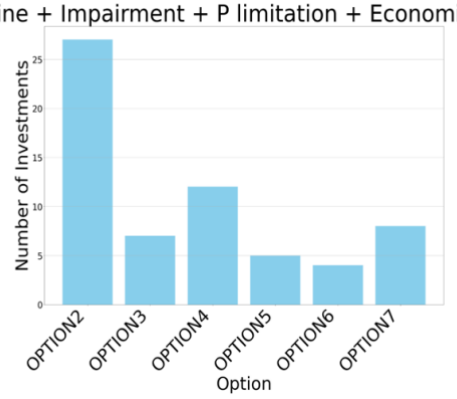

5: Baseline + Economies of Scale
Number of Investments
0
25
50
75
100
125
150
175
200
OPTION6
OPTION7
Option


6: Baseline + Impairment + Economies of Scale
Number of Investments
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
OPTION2
OPTION3
OPTION4
OPTION5
OPTION6
OPTION7
Option

7: Baseline + P limitation + Economies of Scale

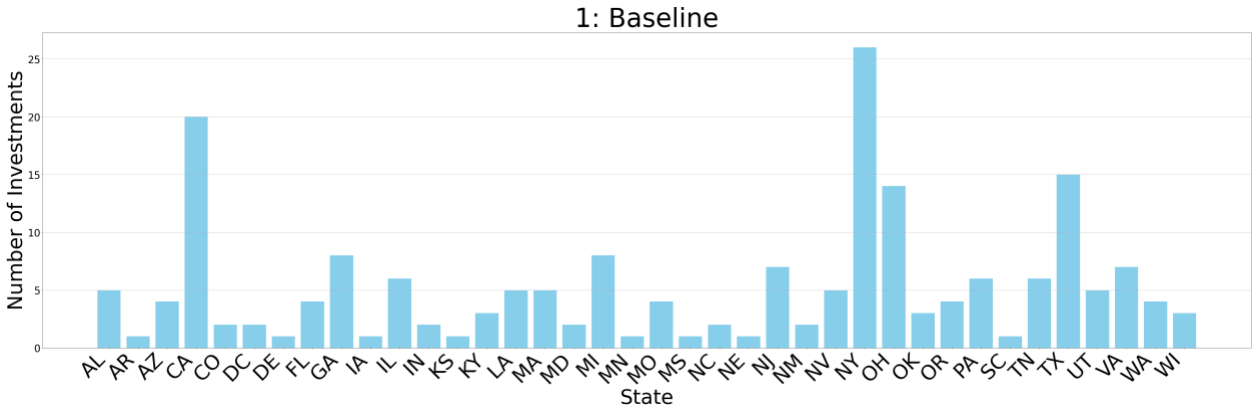


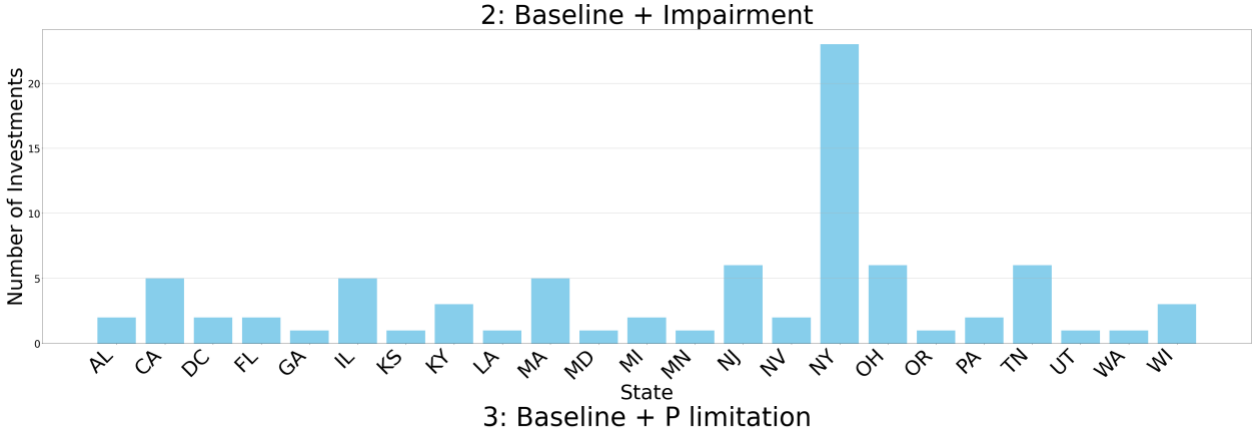
8: Baseline + Impairment + P limitation + Economies of Scale

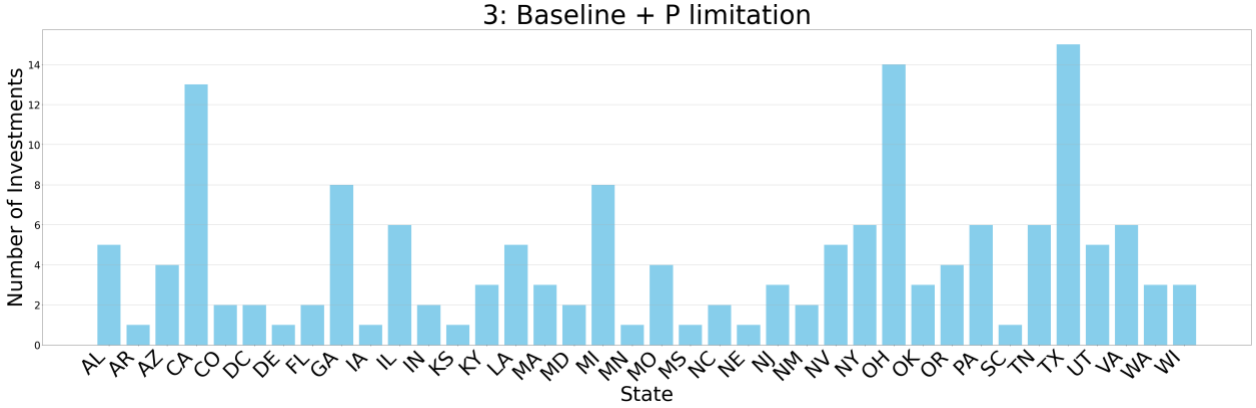


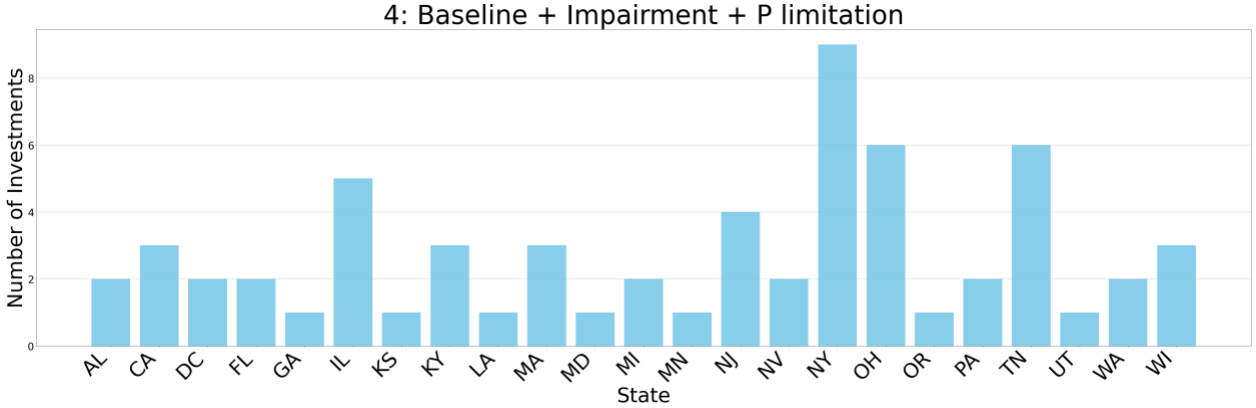
We observe that treatment Option 7 is chosen more often than any of the other treatments (Figure 17, multiple panels). While Option 7 removes less P than other treatments, it has among the lowest capital cost. Even with the economies of scale in Scenarios 5-8, there is not a vast difference in the treatment chosen. Here, we see that the combination of I_p and L_p in Scenarios 4 and 8, produce a greater diversity in treatment options selected. There were no investments made for Options 1 or 8, because of the large cost associated and the relatively low efficiency of the treatments.

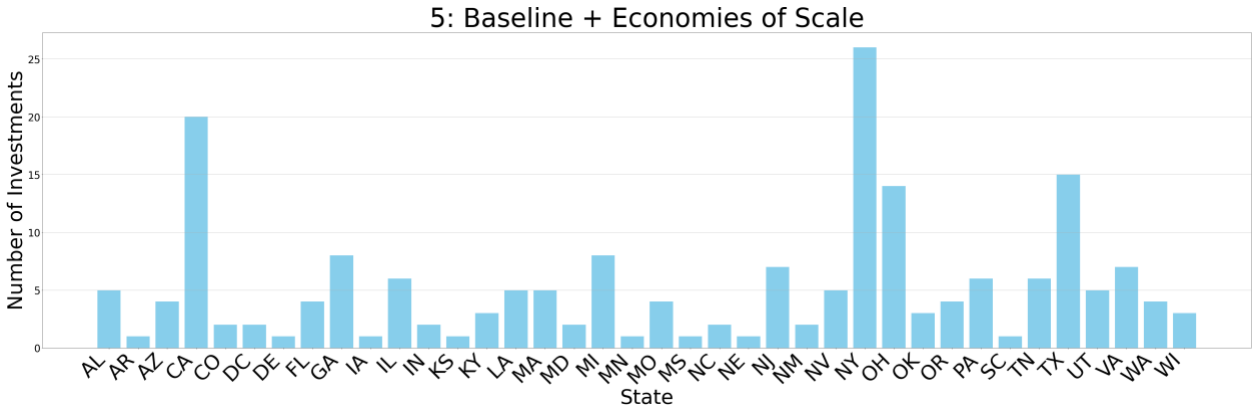
Figure 18 – Number of investments made per state for 8 Scenarios.

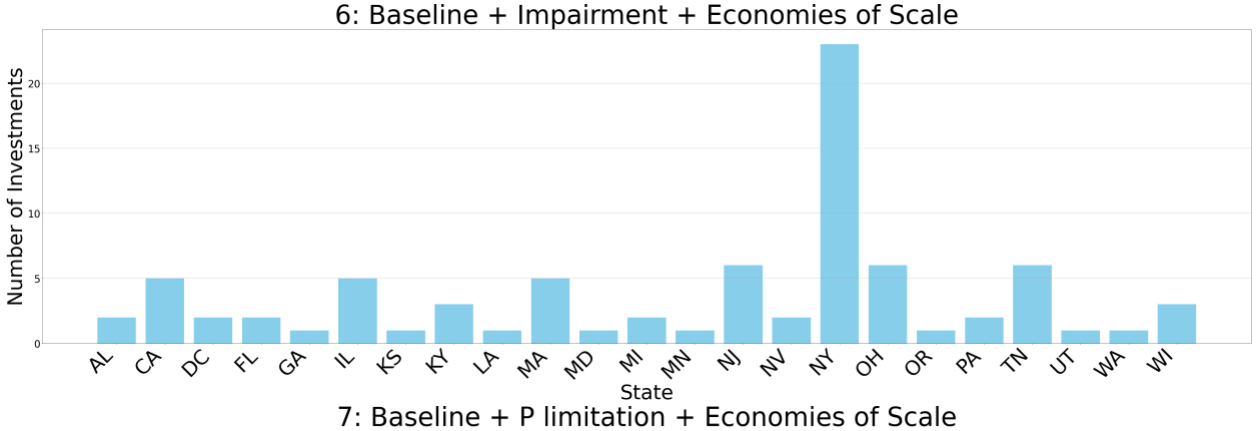

1: Baseline
Number of Investments
0
5
10
15
20
25
AL AR AZ CA CO DC DE FL GA IA IL IN KS KY LA MA MD MI MN MO MS NC NE NJ NM NV NY OH OK OR PA SC TN TX UT VA WA WI
State

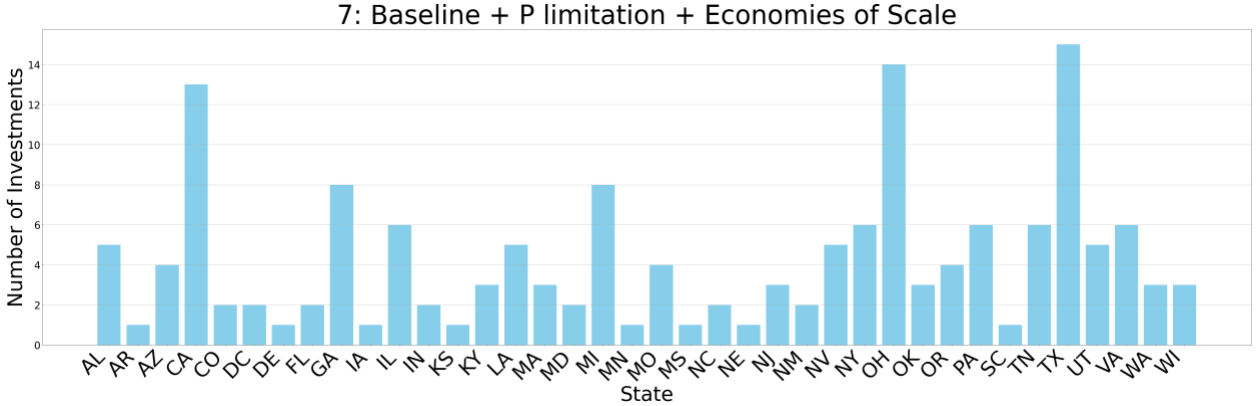

2: Baseline + Impairment
Number of Investments
0
5
10
15
20
AL CA DC FL GA IL KS KY LA MA MD MI MN NJ NV NY OH OR PA TN UT WA WI
State

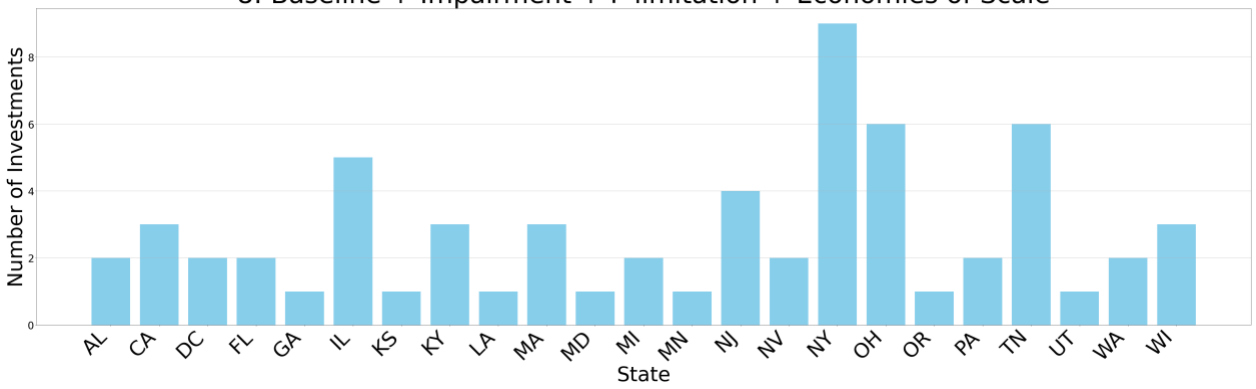

3: Baseline + P limitation
Number of Investments
0
2
4
6
8
10
12
14
AL AR AZ CA CO DC DE FL GA IA IL IN KS KY LA MA MD MI MN MO MS NC NE NJ NM NV NY OH OK OR PA SC TN TX UT VA WA WI
State


4: Baseline + Impairment + P limitation
Number of Investments
0
2
4
6
8
AL CA DC FL GA IL KS KY LA MA MD MI MN NJ NV NY OH OR PA TN UT WA WI
State


5: Baseline + Economies of Scale
Number of Investments
State
AL AR AZ CA CO DC DE FL GA IA IL IN KS KY LA MA MD MI MN MO MS NC NE NJ NM NV NY OH OK OR PA SC TN TX UT VA WA WI


6: Baseline + Impairment + Economies of Scale
Number of Investments
State
AL CA DC FL GA IL KS KY LA MA MD MI MN NJ NV NY OH OR PA TN UT WA WI


7: Baseline + P limitation + Economies of Scale
Number of Investments
State
AL AR AZ CA CO DC DE FL GA IA IL IN KS KY LA MA MD MI MN MO MS NC NE NJ NM NV NY OH OK OR PA SC TN TX UT VA WA WI


8: Baseline + Impairment + P limitation + Economies of Scale
Number of Investments
State
AL CA DC FL GA IL KS KY LA MA MD MI MN NJ NV NY OH OR PA TN UT WA WI

In Figure 18, we see the number of investments made varies for each scenario. New York repeatedly receives many investments in Scenario 1 (7), Scenario 2 (16), Scenario 5 (7), and Scenario 6 (16). However, this is reversed for Scenarios 3 and 7, where New York only receives 1 investment. These scenarios prioritize P limitation and most of the WWTP in New York are within close proximity to the ocean and had high L_p values. Notably, the number of investments remained the same in the models with and without the addition of an economies of scale constraint.

We see a similar drop in the number of investments made in California from Scenario 1, which had 6, to only 2 in the second scenario. California had low levels of impairment and we expected the model's results to reflect these changes. However, California had a high number of investments for Scenario 3 (5), and when both L_p and I_p are prioritized in Scenario 4, the investment is only 2.

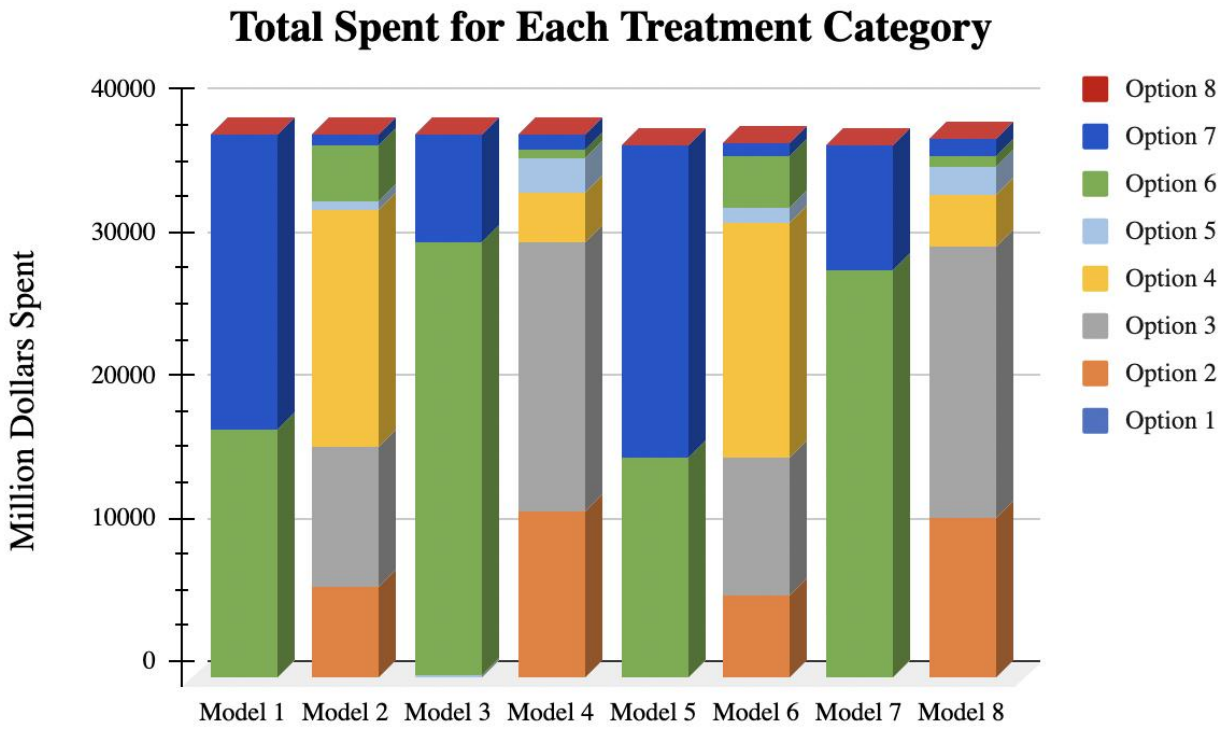
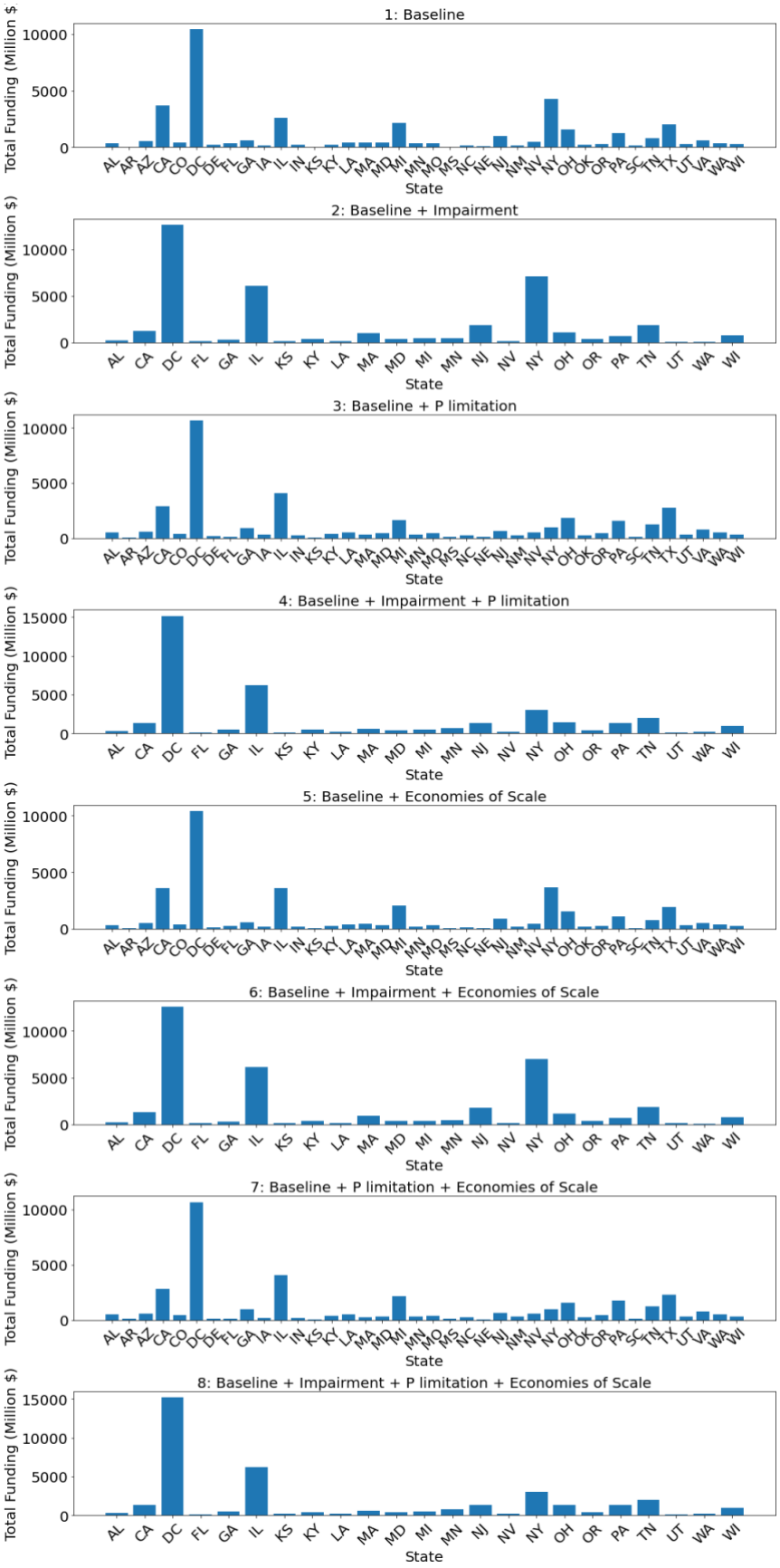


Figure 19 – Total Spent in Million Dollars for Each Treatment Category over 8 Scenarios.

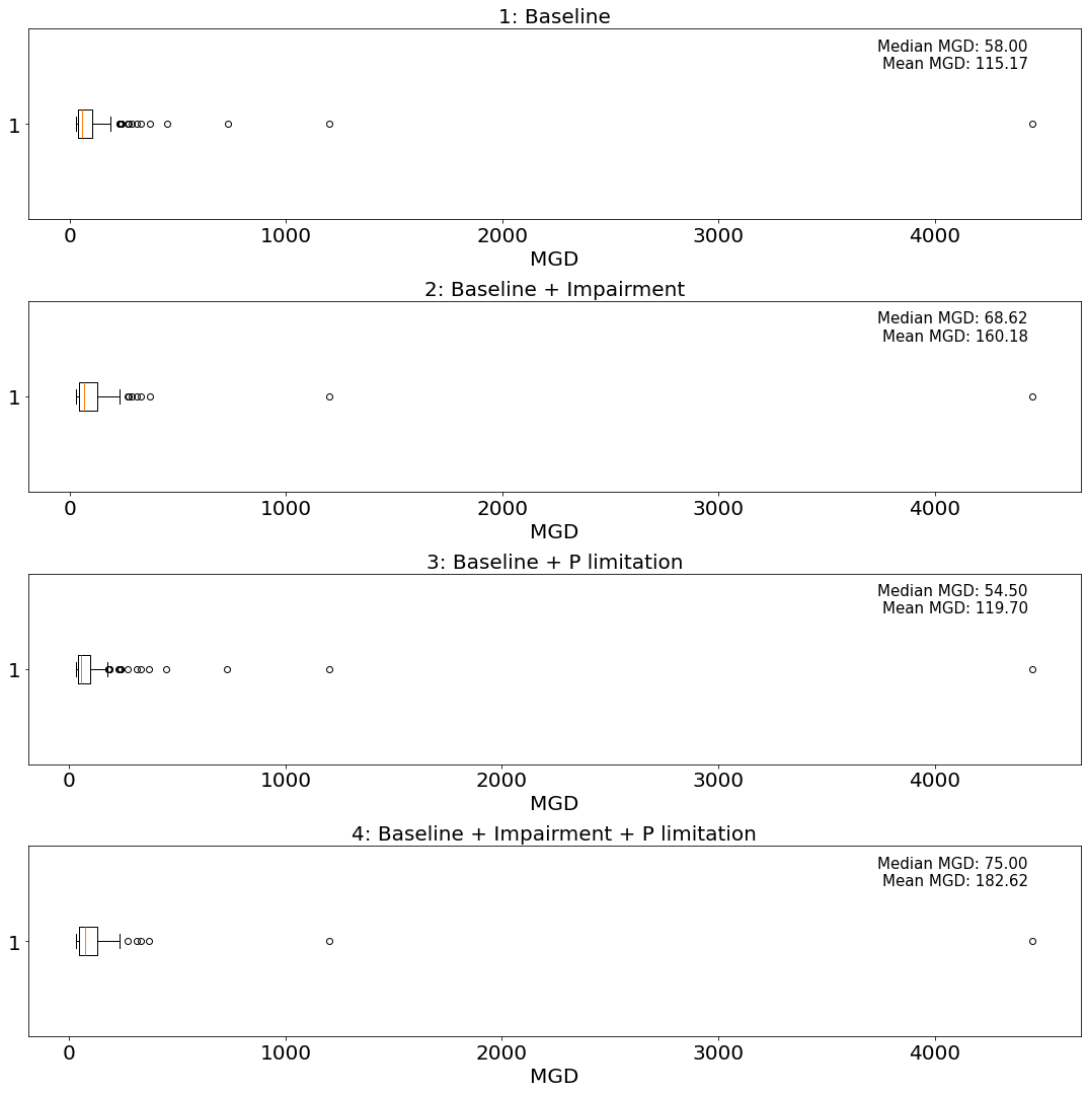
Figure 19 shows the proportion of funds spent in each scenario for specific treatment options. While we see an overwhelming amount of Option 7 chosen in Figure 17, it is the least expensive option and accounts for only a small portion of the total spending. A significantly greater amount of money is spent on Option 2, compared to the other treatment options. With Option 2 having a higher capital cost, this is not unexpected.

Figure 20 – Cost in Million Dollars Spent per State over 8 Scenarios.


1: Baseline
2: Baseline + Impairment
3: Baseline + P limitation
4: Baseline + Impairment + P limitation
5: Baseline + Economies of Scale
6: Baseline + Impairment + Economies of Scale
7: Baseline + P limitation + Economies of Scale
8: Baseline + Impairment + P limitation + Economies of Scale
Total Funding (Million $)
State

The figure above shows there is a large difference in the total amount of money spent per state. DC has significantly more money allocated than any other state, for all 8 scenarios. This is not unexpected, as DC has one of the largest WWTPs in the world, and the largest in the study, at 4453 MGD. Illinois' funding also surpasses other states in all 8 scenarios, behind DC. Illinois has the second largest WWTP in the study with 1200 MGD. When compared to Figure 17, it is clear there is more uniform proportion of the number of investments for each state.

Figure 21 – Box-and-Whisker Plots displaying the WWTP sizes over 8 Scenarios.


1: Baseline
Median MGD: 58.00
Mean MGD: 115.17
1
0
1000
2000
3000
4000
MGD
2: Baseline + Impairment
Median MGD: 68.62
Mean MGD: 160.18
1
0
1000
2000
3000
4000
MGD
3: Baseline + P limitation
Median MGD: 54.50
Mean MGD: 119.70
1
0
1000
2000
3000
4000
MGD
4: Baseline + Impairment + P limitation
Median MGD: 75.00
Mean MGD: 182.62
1
0
1000
2000
3000
4000
MGD

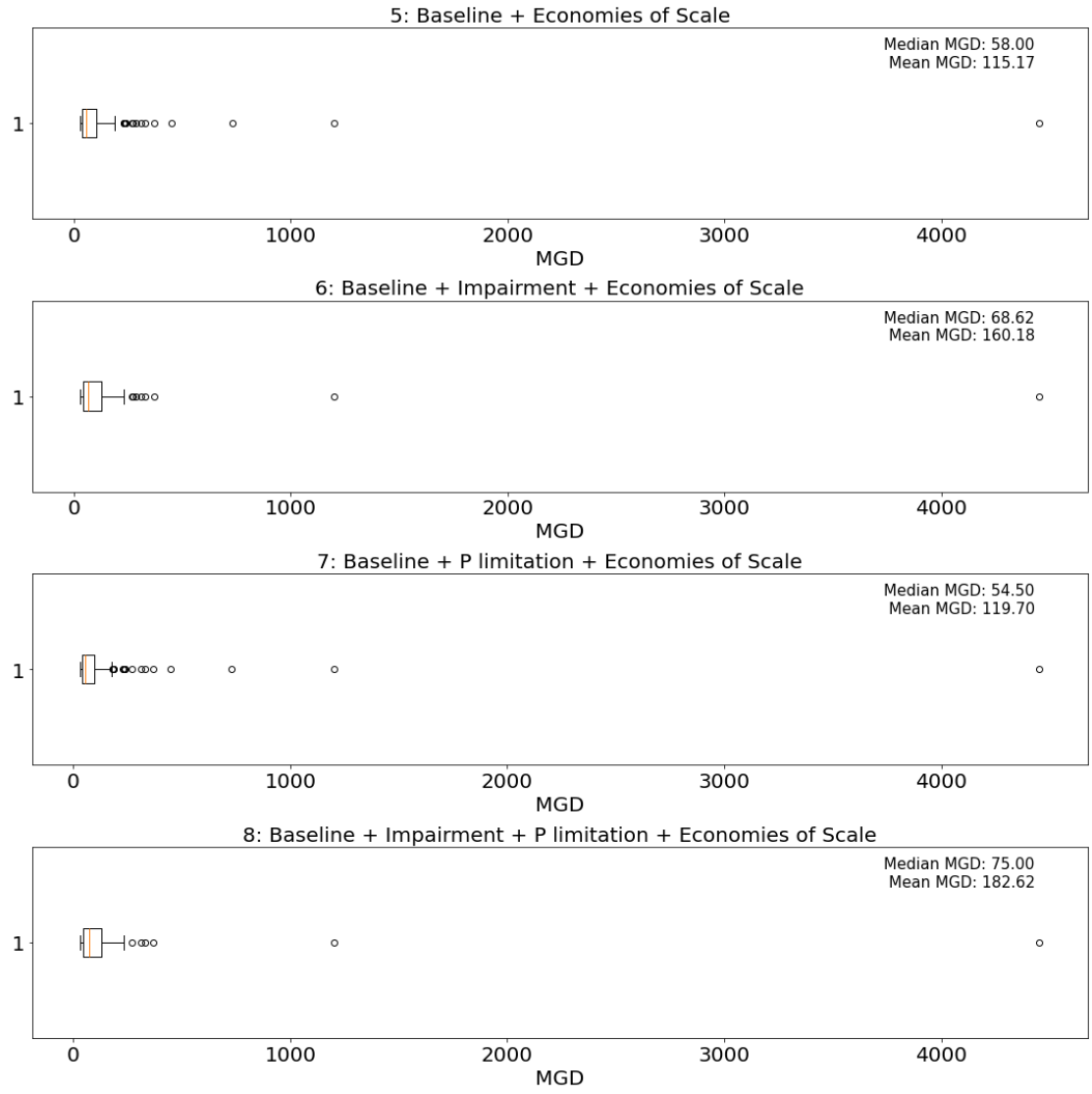

5: Baseline + Economies of Scale
Median MGD: 58.00
Mean MGD: 115.17
1
0
1000
2000
3000
4000
MGD
6: Baseline + Impairment + Economies of Scale
Median MGD: 68.62
Mean MGD: 160.18
1
0
1000
2000
3000
4000
MGD
7: Baseline + P limitation + Economies of Scale
Median MGD: 54.50
Mean MGD: 119.70
1
0
1000
2000
3000
4000
MGD
8: Baseline + Impairment + P limitation + Economies of Scale
Median MGD: 75.00
Mean MGD: 182.62
1
0
1000
2000
3000
4000
MGD

Figure 21 shows the distribution of investments by the size of each plant in MGD. We see a similar result for all 8 scenarios, even when the economies of scale constraint is added. We expected that in the scenarios that account for economies of scale, investment in P removal would be concentrated at large WWTPs. However, when comparing the same model before and after the economies of scale constraint, the mean plant size does not reflect this. For example, Scenarios 1 and 5 show 354.26 and 336.83 average MGD, respectively. However, the mean size decreases after the addition of the economies of scale constraint. Scenarios 2 and 6 are the only models that show an increase in the average plant size after the addition of the economies of scale constraint, with values at 215.76 and 219.24 MGD.

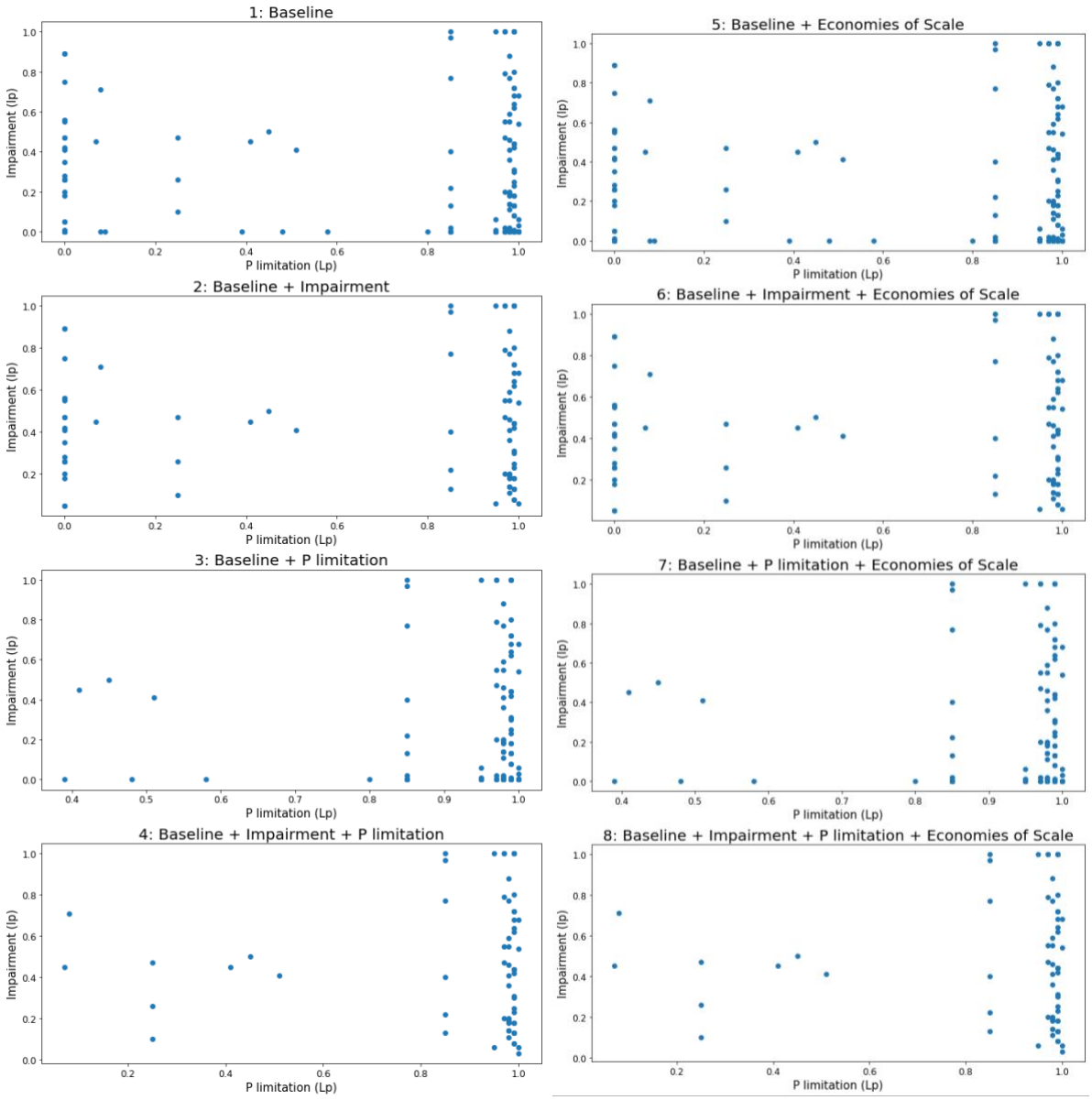


Figure 22 – Scatter plots of Ip values versus Lp values for WWTP selected for investment.

In Figure 22, each point represents a WWTP investment and the respective Ip and Lp values. All eight subplots show a pattern clustering where Lp values are high, especially for Scenarios 3 and 7, where the Lp is prioritized. Scenarios 3 and 7 shows a much higher Lp value, compared to the more uniform dispersal in the baseline scenarios. As for impairment, there is a uniform dispersal for all eight subplots, even for the scenarios in which impairment is prioritized. Between

plots 1 and 2, and 5 and 6, we do see a small decrease the number of plants selected with low impairment values, favoring higher impairment values less than expected.

Conclusion

Our study compared the results for eight scenarios in which the objective function and constraint were altered. We found that there is a potential for this type of optimization to be used in decision making when presented with multiple objectives and tradeoffs given a limited budget. With our altered objective functions, we found impairment status to be the most important factor for determining the treatment option but was less influential on plant location selection than expected. P limitation, however, was impactful on the selection of sites with higher Lp values when solely considered and we saw a variation in the number of states with investments. We expected economies of scale to have a larger impact on the size of the plants chosen. Economies of scale did not have a significant impact on the mean size of selected WWTPs but did impact the treatment option selected.

A major takeaway from this study is the lack of national datasets suitable for use in optimization models was a significant hindrance for this type of research. While designing the study, we aimed to include additional objectives such as downstream dilution factors and distinguishing between watersheds polluted by non-point sources of P. However, we found a lack of quantitative, publicly available data, specifically regarding national phosphorus pollution levels and sources, nutrient limitation, downstream impacts, and potential value in recovery. For example, the P limitation status in this study was determined by using salinity as a proxy. If the P limitation had been quantified and separated by source, such as agricultural runoff, then our model could make more accurate decisions about where the most effective location for technology implementation is.

Given more accessible data, such as the condition of watersheds surrounding our WWTPs, updated capital costs, current removal technologies, and the potential cost incentive for recovery, the models could have additional complexity and more applicable results.

Future research into how promote equity amongst the distribution is needed, such as an objective to minimize the differences in water quality improvement across states or by watershed. On the other hand, future research could explore environmental justice and investigate investments for the states with the greatest need for water quality improvement and funding. This study looks at results by state, but future studies could also investigate by watershed, as many watersheds cross state lines and their improvement is shared by more than one state. An additional venue for research that we were not able to fully explore is the inclusion of O&M costs, rather than only initial capital costs, to better understand the perspective for each WWTP's operation and management.

REFERENCES

A compilation of cost data associated with the impacts and control of nutrient pollution | US EPA. (n.d.-a). https://www.epa.gov/nutrient-policy-data/compilation-cost-data-associated-impacts-and-control-nutrient-pollution

Cooper, J., Lombardi, R., Boardman, D., & Carliell-Marquet, C. (2011). The future distribution and production of global phosphate rock reserves. *Resources, conservation and recycling*, *57*, 78-86.

Correll, D. L. (1998). The role of phosphorus in the eutrophication of receiving waters: A review. *Journal of environmental quality*, *27*(2), 261-266.

Cordell, D., Drangert, J. O., & White, S. (2009). The story of phosphorus: global food security and food for thought. *Global environmental change*, *19*(2), 292-305.

Cordell, D., Rosemarin, A., Schröder, J. J., & Smit, A. L. (2011). Towards global phosphorus security: A systems framework for phosphorus recovery and reuse options. *Chemosphere*, *84*(6), 747-758.

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N., & Smith, V. H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological applications*, *8*(3), 559-568.

Environmental Protection Agency. (2017). EPA. https://www.epa.gov/waterdata/national-water-quality-inventory-report-congress

Dodds, W. K., Bouska, W. W., Eitzmann, J. L., Pilger, T. J., Pitts, K. L., Riley, A. J., ... & Thornbrugh, D. J. (2009). Eutrophication of US freshwaters: analysis of potential economic damages.

Harper, D. M. (1992). Eutrophication of freshwaters.

Hernández-Chover, V., Bellver-Domingo, Á., & Hernández-Sancho, F. (2018). Efficiency of wastewater treatment facilities: The influence of scale economies. *Journal of environmental management*, *228*, 77-84.

Howarth, R. W., & Marino, R. (2006). Nitrogen as the limiting nutrient for eutrophication in coastal marine ecosystems: evolving views over three decades. *Limnology and oceanography*, *51*(1part2), 364-376.

How's my waterway: A tool for exploring your water quality | US EPA. (n.d.). https://www.epa.gov/green-infrastructure/hows-my-waterway-tool-exploring-your-water-quality

Islam, M., (2023) *Science and Technologies for Phosphorus Sustainability (STEPS) Presentation*

Infrastructure Investment and Jobs Act, Pub. L. No. 117-58 (2021).

Ji, X. (2022). *Optimization of Best Management Practices to Reduce Phosphorus Runoff in the Grand River Watershed Using a Multi-Objective Optimization Algorithm* (Master's thesis, University of Waterloo).

Liu, Y., Villalba, G., Ayres, R. U., & Schroder, H. (2008). Global phosphorus flows and environmental impacts from a consumption perspective. *Journal of Industrial Ecology*, *12*(2), 229-247.

Newman, A. (1995). Water pollution point sources still significant in urban areas. *Environmental Science & Technology*, *29*(3), 114A-114A.

Ogneva-Himmelberger, Y., Huang, L., & Xin, H. (2015). CALPUFF and CAFOs: air pollution modeling and environmental justice analysis in the North Carolina hog industry. *ISPRS international journal of geo-information*, *4*(1), 150-171.

Parsons, S. A., & Smith, J. A. (2008). Phosphorus removal and recovery from municipal wastewaters. *Elements*, *4*(2), 109-112.

Puckett, L. J. (1995). Identifying the major sources of nutrient water pollution. *Environmental Science & Technology*, *29*(9), 408A-414A.

Sarvajayakesavalu, S., Lu, Y., Withers, P. J., Pavinato, P. S., Pan, G., & Chareonsudjai, P. (2018). Phosphorus recovery: a need for an integrated approach. *Ecosystem health and sustainability*, *4*(2), 48-57.

United States. Environmental Protection Agency. EPA. https://www.epa.gov/water-research/freshwater-explorer

United States. Environmental Protection Agency. Office of Wastewater Management. Municipal Support Division, National Risk Management Research Laboratory (US). Technology Transfer, & Support Division. (2004). *Guidelines for water reuse*. US Environmental Protection Agency.

Zhang, M., & Batjargal, T. (2022). Review on new spending of United States bipartisan infrastructure bill. *Journal of Infrastructure, Policy and Development*, *6*(2), 1507.

Zheng, F., Zecchin, A. C., Maier, H. R., & Simpson, A. R. (2016). Comparison of the searching behavior of NSGA-II, SAMODE, and Borg MOEAs applied to water distribution system design problems. *Journal of Water Resources Planning and Management*, *142*(7), 04016017.