



The potential impact of forest loss on drinking water treatment costs in the southeastern U.S.

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ABSTRACT

Previous research shows that forest preservation can protect water quality, but it is less clear what the net economic costs of forest preservation might be for drinking water utilities. Economic valuation of forest benefits for drinking water is complex in part because the potential economic benefit is indirectly related to forest preservation through the benefit of forests for water quality. We contribute to a growing literature on land use-water quality interactions by linking ecological production and economic valuation functions that relate to changes in forest cover and water quality. We estimate potential avoided drinking water treatment costs by analyzing water quality impacts of projected land use change, using changes in nutrient concentrations. Specifically, we use observations from a survey conducted in the Southeastern US to explore which factors influence the variation in reported treatment costs. We then integrate the primary data with simulated outputs from a detailed ecological production function to project the potential long-term cost implications of land use change (including forest loss) in the region. Our findings suggest that a 1 % reduction in turbidity and TOC would reduce treatment costs by 0.046 %–0.091 % and 0.951 %–1.144 %, respectively. Further, while we find evidence of modest net cost impacts overall (<10 % for most facilities) under potential future land use change, we find a 1 % forest loss could increase treatment costs by 1.7 %. These results highlight the potential economic value of forest preservation in water supply systems and could inform source water protection strategies by water utilities through forest management incentives. **Keywords:** Forest Loss, Water treatment costs, Water quality.

1. Introduction

A significant and growing literature acknowledges the important role that forests play in hydrologic processes and in maintaining and improving water quality (Caldwell et al., 2023; Vose, 2019; Gartner et al., 2014). Forested land cover is generally associated with lower levels of nutrient and sediment loads relative to agricultural or developed lands. Thus, understanding the trade-offs between forest land use and land development is crucial for supporting water-related ecosystem

services when degradation of downstream water quality is a concern (Vose, 2019; Riitters et al., 2023). Regions like the Southeastern United States, with a high proportion of forest area but rapid development patterns in urban and suburban areas, could experience degraded water quality and increased water treatment costs for public drinking water systems (Warziniack et al., 2017; Caldwell et al., 2023). Liu et al. (2021) suggest that higher water yield and runoff associated with forest disturbance could come at the expense of water quality and, hence, increase water treatment costs. Previous projections suggest forestland

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across the South could decrease by 44,515–89,030 km² between 1997 and 2060 depending on socioeconomic conditions (Wear and Greis, 2013). Moreover, 87 % of forested land in the Southern United States is privately owned, further exacerbating the pressure from the expansion of developed land given the financial benefits of conversion to urban land for landowners (Wear and Greis, 2013; Liu et al., 2021). Public policies and private investment in forest preservation may be needed to negate the water-related impact of forest loss, and some public water supply systems are actively investing in forest protection in upstream watersheds in the interest of source water protection (Gartner et al., 2017; Postel and Thompson Jr., 2005). Indeed, a recent survey among more than 2400 water utilities in the United States revealed that source water protection is now the top concern among these utilities (AWWA, 2024). Compliance markets for watershed protection have been estimated at approximately \$1 billion per year on average for 2015–19 in the U.S., mostly in the southeastern states (Frey et al., 2021).

The quantification of water quality benefits of forested watersheds involves disentangling the linkages between land use and hydrology. Doing so becomes complex as the scale of analysis shifts from small and individual watersheds to multiple watersheds at broad spatial scales (Holmes et al., 2017). One solution to overcoming the complexity of the relationship lies in assuring that the final ecosystem services are measured using the same indicators as the valuation functions (Holmes et al., 2017; Olander et al., 2015).

Water quality benefits of forests manifest as a reduction in the treatment cost (short-term variable cost) at the water treatment plant due to an improvement in the source water quality (factor input). This is similar to the goal of a profit-maximizing firm where the choice of variable inputs is made to minimize the production costs for a fixed level of outputs (Price and Heberling, 2018). While recent research indicates that forest preservation in rapidly urbanizing regions like the southeastern U.S. can offer water quality protection services (Caldwell et al., 2023), it is less clear what the net costs and benefits of forest preservation might be for drinking water utilities or other water resource consumers in the region. We calculate these cost functions using methods based on previous literature (Warziniack et al., 2017), specifically for the Southeastern US. We take a step further and link the survey data to modeled water quality data, addressing the gap in the methodological approach which limits analyses to survey responses. Finally, we use the ecological and economic functions estimated in this study (as well as in Caldwell et al., 2023) to project future water treatment cost changes based on commonly used scenarios of future change. This study contributes to a growing literature on land use change (LUC) and water quality interactions by linking ecological and economic production functions that relate changes in forest cover and water quality to potential changes in water treatment costs. Specifically, our overall goal was to estimate the value of water quality improvements via avoided LUC on public drinking water systems in terms of avoided water treatment costs. We focus on the following research questions- What are the factors that are most influential in driving the variation between the treatment costs? How would the projected land use and population changes impact the future treatment cost projections? The study aims to identify avoided treatment cost hotspots, i.e., the regions where preserving forests would significantly impact the treatment costs. We first develop cost estimates from a targeted survey of drinking water treatment plants located in the southeastern U.S. Using the survey results, we quantify which physical and economic factors are most influential in driving variation in reported treatment costs. Factors considered in the study include an estimated change in water quality at intake locations under alternative LUC scenarios, intake watershed characteristics, and other facility-specific infrastructure and cost factors. We then link those models to future projections of future LUC to estimate potential avoided treatment costs across the region.

This study makes several contributions to literature. First, we provide updated estimates of avoided drinking water treatment costs in a rapidly developing region of the U.S., which could be used to support

decision-making within the region or benefit transfer studies for valuation or policy applications outside of the U.S. Southeast. Second, we integrate primary data collection methods (survey) with simulated outputs from a detailed ecological production function to project the potential long-term cost implications of LUC in the region, drawing from recent LUC projections from the USDA Forest Service Resources Planning Act Assessment (USFS, 2023). This approach presents a methodological advancement that helps reconcile key differences between economic valuation functions and ecological production functions, specifically related to how water quality data are collected, reported, and modeled. Most water treatment plants in our survey, and in general, collect information on total organic carbon (TOC) and/or turbidity at the water intake point, but often do not directly observe total nitrogen (TN), phosphorus (TP), or suspended sediment (TSS), which are parameters the environmental modeling community typically simulate at watershed scales. We use the spatially explicit LUC projections for 2020 and 2070 to estimate TN and TP concentrations at the intake facilities using land use-water quality regressions developed in Caldwell et al. (2023) that relate TN and TP to upstream percentages of developed, forest, agriculture, and other natural land use. Estimated intake-level TN and TP concentrations were then used to calculate the percentage change in nutrients from current business as usual (BAU) conditions is thus reflective of potential changes in costs associated with a change in nutrient loads from current conditions. Linking simulated ecological data with survey responses helps reconcile this inconsistency and allows for a region-wide assessment of potential treatment cost impacts of future LUC.

Results from the survey show an increase in treatment costs with increases in turbidity and TOC measured at the intake facility and other estimated parameters that conform to economic logic. We estimate a separate cost function using simulated nutrient concentrations at each facility, leveraging the approach summarized in Caldwell et al. (2023). We spatially extrapolate cost estimates from the nutrient cost function across the south and then estimate the potential impact of future forest loss on facility-level treatment costs.

Our findings suggest that a reduction of 1 % in turbidity and TOC would result in 0.046 %–0.091 % and 0.951 %–1.144 % of water treatment costs. However, when we link our survey results with ecological projections of nutrient flow under future land use change scenarios, we find evidence of both increased and decreased treatment costs, suggesting spatial heterogeneity contextual differences in potential future impacts of LUC on drinking water utilities. These results highlight the potential economic value of forest preservation for water quality maintenance. Finally, we discuss the policy implications of our findings and provide areas for future research and analysis. We provide uncertainty ranges for our projected cost changes across different groups of facilities in the appendix (section 10.11).

The next section gives a brief review of literature studying water treatment cost-water quality-forest cover relationships. Section 4 describes the modeling framework, data, and methodology used for the analyses, and Section 5 presents different results from our econometric models and projected future land use models. Section 6 briefly discusses the computed results and then concludes.

2. Literature review

There has been limited research on the relationship between water treatment cost and source water quality and even less on the economic value of forest conservation (avoided water treatment costs). Much of this research is in the form of white papers and government reports and the studies that exist face a shortage of available data. An alternate approach could be combining behavioral and engineering cost models to replace unavailable datasets (Price and Heberling, 2018). The data required to quantify the links between source water quality and treatment costs are typically in the form of non-random samples and laborious primary collection. Cross-sectional analysis in this research has

included less than 50 observations (Ernst et al., 2004; Freeman et al., 2008; Mosheim and Ribaud, 2017; Oklahoma Water Resources Board, 2011a; Renzetti, 2001; Warziniack et al., 2017).

The literature linking forest cover to water treatment costs typically does so in a two-step fashion- first identifying the ecological relationship (often called the ecological production function) between forest cover and water quality, then identifying the economic benefit function related to those changes (Holmes et al., 2017; Warziniack et al., 2017; Hascic and Wu, 2006; MacDonald and Coe, 2007; Forster and Murray, 2007). In this approach, the avoided treatment costs are thus expressed as lower-bound estimates of the ecosystem service benefits of natural lands. Hence, only the factors directly affecting the facility operations are included in the cost function, while land use is accounted for indirectly (Price and Heberling, 2018). This strand of literature focuses on two important ways in which forests reduce drinking water costs. Vegetation in forests provides regulatory ecosystem services that stabilize flows and filter the water flowing through them, leading to cleaner and more predictable raw water at drinking water intakes (Piper, 2003; Warziniack et al., 2017; Piaggio and Siikamäki, 2021). Forests also serve as buffers, keeping other polluting activities out of the watershed (e.g., agriculture and development) (Abildtrup et al., 2013; Brown and Froemke, 2012).

Dearmont et al. (1998), Forster and Murray (2007), and Warziniack et al. (2017) have focused on the relationship between expenditures on treatment chemicals and source water quality changes. Few studies have introduced broader definitions of costs, i.e., including all variable and capital inputs (Horn, 2011; Ernst et al., 2004; Renzetti, 2001).

Table 1 describes the most common water quality, land use, and control variables employed in literature. Turbidity is the most commonly included variable since it is universally monitored and is utilized by water treatment plants and their operators for compliance regulations and facility operations (Price and Heberling, 2018). A few studies have not included any control variables (Ernst et al., 2004; Freeman et al., 2008; Honey-Ros'es et al., 2014; McDonald and Shemie, 2014; Oklahoma Water Resources Board, 2011a).

The economics of avoided treatment costs via forest management and preservation is highlighted in several studies, but few have quantified the net impact of forest preservation on water-related ecosystem services and water treatment costs (Gartner et al., 2014). Associations like the American Water Works Association and the US Endowment for Forestry and Communities are furthering research on the relationship between treatment costs and forest cover and building partnerships with water utilities to protect forested watersheds (Gartner et al., 2014). Cities like New York, Boston, Tokyo, and Sao Paulo have started forest

conservation policies to provide drinking water (Price and Heberling, 2018; McDonald and Shemie, 2014; Gartner et al., 2014). However, the costs of source water protection are highly varied and could be as high as several hundred dollars per hectare (McDonald and Shemie, 2014; Price and Heberling, 2018; Heberling et al., 2015), indicating that source water protection costs can exceed the benefits for some wastewater treatment plants (Price and Heberling, 2018).

Evidence thus suggests that source water protection may not be cost-effective if avoided water treatment costs are the only benefits included, thus research is needed to not only account for other benefits such as reduced wildfire risk, wildlife habitat, carbon storage, aesthetics, improved recreation services, etc., but also to include different water quality parameters which may impact water use for recreation, fish and wildlife, and overall ecosystem function but have little impact on drinking water treatment costs (e.g., harmful algal and cyanobacterial blooms) (Price and Heberling, 2018). Accounting for a range of ecosystem service benefits and associated uncertainty is also critical for designing effective incentive structures designed to maintain or increase water-related benefits of forests (Valatin et al., 2022).

3. Materials and methods

3.1. Modeling framework (conceptual approach)

We used the overall framework provided by Holmes et al. (2017) to guide our work. In this framework, the final ecosystem service provided by forests is clean and stable source water for water utilities. This ecosystem service is dependent on many primary and secondary processes (e.g., socioeconomic and land use dynamics, upstream inputs, land use legacy, etc.) that affect water quantity and quality. These relationships, known as Ecosystem Service Production Functions, are typically studied using land use-water quality regressions or hydrological modeling. The Ecosystem Service Production Functions inform an Economic Valuation Function that is used to assess the economic value of the final ecosystem service based on drinking water use. We linked water quality with land use using an ecosystem service production function from Caldwell et al. (2023). The ecosystem service production function draws on the precedent of analysis developed by Warziniack et al. (2017). Fig. 7 in the Appendix presents a general conceptual representation of how the various modeling components in this analysis fit together.

3.1.1. Linking ecological/ecosystem service production and economic valuation functions

Water quality is the final forest ecosystem service that benefits human beings who consume it. We consider two water quality indicators in this study that are reported by the survey responses received: turbidity and TOC, as well as simulated concentrations of total nitrogen (TN), total Phosphorus (TP), and total suspended solids (TSS). For the baseline conditions corresponding to the time of the survey of utilities, we used simulated TN and TP concentrations detailed in Caldwell et al. (2023) that were based on published SPATIALLY Referenced Regression On Watershed (SPARROW) model outputs developed by the U.S. Geological survey. For projections of future treatment costs under land use change scenarios, we used multiple regression models from Caldwell et al. (2023) that relate the percentages of upstream developed, forest, agriculture, and other natural land use to TN and TP concentration (see Appendix, section 10.1). These regression models were developed using observed nutrient concentration data from more than 1300 monitoring sites across the South.

3.1.2. Economic valuation function

In this study, we create two different economic valuation functions. The first estimates the relationship between treatment costs and water quality variables observed by different water treatment plants, i.e., Turbidity and TOC, and reported by the utilities. The second describes

Table 1

Variables and measures included in previous studies linking land use, water quality, and drinking water treatment costs. Turbidity-Treatment Cost and Turbidity-Forest cover are the most common relationships studied in the previous studies. We included the most common indicators based on previous studies.

Variable	Measures	Studies
Water Quality	Turbidity, Total Organic Carbon (TOC),	Warziniack et al., 2017; McDonald et al., 2016; Piaggio and Siikamäki, 2021;
	Water Hardness	Piper, 2003
	Water Quality Index	Freeman et al., 2008, Renzetti, 2001
Land use	Forestland, Agriculture, Urban,	Abildtrup et al., 2013; Lopes et al., 2019; Figuepron et al., 2013;
	Rangeland, Barren-land, Grassland	Warziniack et al., 2017
Explanatory factors	Volume of treated Water	Holmes, 1988; Price et al., 2017; Mosheim, 2006; Renzetti, 2001;
	Some combination of labor, chemical and energy prices	Mosheim and Ribaud, 2017; Horn, 2011; Price and Heberling, 2018

similar relationships between simulated TN and TP from [Caldwell et al. \(2023\)](#) and treatment costs enabling us to link water quality variables not reported by most facilities.

Water utilities choose quantities of variable inputs in the short run while keeping capital inputs fixed. They strive to minimize costs while maintaining the regulatory water quality mandates ([Warziniack et al., 2017](#)). Source water quality Q_i impacts the treatment costs, $Cost_i$, through both chemical costs and the choice of treatment technology. The utilities in our study typically use either conventional treatment methods or advanced treatment methods, which vary in terms of both cost and effectiveness. The conventional filtration system includes processes such as coagulation, flocculation, sedimentation, granular media filtration (e.g., Sand, anthracite, etc.), and disinfection. On the other hand, the advanced systems involve two steps: i) pre-treatment for solids removal and ii) membrane filtration for particles or dissolved constituents ([Warziniack et al., 2017](#)).

Apart from source water quality and the treatment processes, the volume of water ($DailyProd_i$) treated at a facility also determines the costs of treating raw water. The size of the treatment plant is not only measured by the volume of water treated at the facility but also by the number of people served by the facility. Finally, we assume a non-linear relationship between water quality and chemical costs by including their logarithmic transformations in our model specification. We also account for economies of scale in water treatment by adding a variable and interaction term for population served, where $HighDen_i$ takes the value 1 if the treatment plant serves a population of greater than 5000 and 0, otherwise.

Hence, the economic valuation function using Turbidity (T) and TOC as water quality variables is given by:

$$\begin{aligned} \log(Cost_i) = & \beta_0 + \beta_T (\log(T_i)) + \beta_{TOC} (\log(ToC_i)) + \beta_{hd} HighDen_i \\ & + \beta_a Advanced_i + \beta_c Coventional_i + \beta_{prod} DailyProd_i \\ & + \beta_{pd} DailyProd_i * HighDen_i + \varepsilon_i \end{aligned} \quad (1)$$

where β_0 is the intercept term and β_x are the coefficients of various independent variables. $Cost_i$ represents the average annual chemical (variable input cost) cost per million gallons of water treated, $Advanced_i$, and $Coventional_i$ indicate whether a treatment plant uses advanced and conventional filtration systems respectively, $DailyProd_i$ controls for the average daily production of water at the plant, and ε_i is an error term.

To link ecological production and economic valuation functions across all water utilities in the region, we ran a similar series of regressions that use simulated water quality data for each facility in our survey dataset. The key difference with this functional form is that we replaced simulated TN and TP for TOC and turbidity to better align with ecological models that are designed to simulate changes in nutrient or sediment flow and not turbidity/TOC. We used the US Geological Survey SPARROW simulated nutrient concentrations as reported in [Caldwell et al. \(2023\)](#) for the public water systems that responded to our surveys.

The economic valuation function for nutrients is given by:

$$\begin{aligned} \log(Cost_i) = & \beta_0 + \beta_N (\log(N_i)) + \beta_P (\log(P_i)) + \beta_{hd} HighDen_i \\ & + \beta_{river} river_i + \beta_a Advanced_i + \beta_c Coventional_i + \beta_{prod} DailyProd_i \\ & + \beta_{pd} DailyProd_i * HighDen_i + CumArea_i + \varepsilon_i \end{aligned} \quad (2)$$

where, N_i and P_i represent TN and TP concentration, $CumArea_i$ represents the cumulative upstream catchment area, $DailyProd_i$ is average daily water production, and the remaining terms represent indicator variables reflecting population density and treatment technologies.

3.1.3. Future cost projections

Finally, we project future cost changes under LUC to assess the spatial heterogeneity of projected land use change on water treatment costs using a cost model that applies regression coefficients from the nutrient valuation functions.

We use the database of 1361 public water systems summarized in

[Caldwell et al. \(2023\)](#) and their current physical attributes (including average nutrient concentrations) to interpolate average annual treatment costs per facility (dollars per MGD).¹ For public water systems with more than one intake facility, we assumed that the intake facility among these with the largest watershed area was representative of the public water system. Then, we project costs under future conditions, assuming varying levels of socioeconomic development (population growth), projected land use change, and projected changes in nutrient and sediment flows. We used land use projections developed as part of the USDA Forest Service 2020 Resources Planning Act (RPA) Assessment ([USFS, 2023](#)) to assess how future LUC could impact water quality at public water system drinking water intakes. The 2020 RPA projects land use from 2020 to 2070 on a decadal basis, focusing on the effects of both socioeconomic and climatic change on land use across 20 combinations of four Shared Socioeconomic Pathways (SSP) and five general circulation models (GCMs) in the IPCC Fifth Assessment Report (Intergovernmental Panel on Climate Change (IPCC), 2014). We selected two of the SSP scenarios (SSP3 and SSP5) to capture a range in projected population and economic growth assumptions coupled with two climate scenarios (HadCEM2-ES and MRI-CGCM3) that capture a range in potential future climatic conditions under the Representative Concentration Pathway (RCP) 8.5. SSP3 represents assumptions of relatively low GDP and population growth in the U.S., while SSP5 represents assumptions of relatively high U.S. GDP and population growth. Meanwhile, the HadCEM2-ES GCM (hereafter HAD) GCM was considered a “hot” climate model for the U.S., while the MRI-CGCM3 GCM (hereafter MRI) GCM was considered the “least warm” model ([USFS, 2023](#)). Together, the two SSPs and two GCMs result in four future land use scenarios for this study: MRI SSP3 (low growth, low warming), MRI SSP5 (high growth, low warming), HAD SSP3 (low growth, high warming) and HAD SSP5 (high growth, high warming). These four scenarios were selected to provide a broad range of potential socioeconomic (SSP3 low and SSP5 high) and climate (MRI-CGCM3 least warm and HADCEM2-ES hot) future conditions.

We use the spatially explicit LUC projections for 2020 and 2070 to estimate TN and TP concentrations at the intake facilities using land use-water quality regressions developed in [Caldwell et al. \(2023\)](#) (See Appendix section 10.1). Estimated intake-level TN and TP concentrations were then used to calculate the percentage change in nutrients from current BAU conditions is thus reflective of potential change in costs associated with a change in nutrient loads from current conditions. While the land use projections were informed by climate projections, we did not simulate water quality responses to changes in climate (i.e., precipitation and temperature). Thus, our projections of TN and TP concentration and treatment costs only isolate the effects of land use change only under future scenarios.

We also used county-level estimates of population growth from 2020 to 2070 from the RPA and mapped these to the service area for each treatment plant and for each scenario. We used USGS estimates of per-capita water use from the public supply sector in 2015 ([U.S. Geological Survey, 2020](#)) to estimate per-capita water consumption and thus average daily production for each water utility. Total water consumption in 2070 for each facility service area is then scaled accordingly, holding per capita consumption fixed over time. We then use this estimate of future water consumption to scale the average daily production variable proportionately for each facility. Our final cost impact estimates then become the difference between projected costs with future LUC, nutrient, and population change relative projected costs under current land use and nutrient loads, but with projected future population in 2070 for each scenario. This process helps us to isolate the effect of LUC and water quality changes from the potential treatment cost impacts of serving a larger local population.

Our scenario-based approach is different than a one-at-a-time

¹ We acknowledge this limitation of the study.

sensitivity analysis around a particular set of parameters or a Monte Carlo simulation framework, but it is an appropriate approach for projecting a plausible range of future water treatment cost impacts under future land use changes. We further analyze uncertainty in projected cost impacts through a bootstrapping routine to produce confidence intervals around groups of facilities, which can be found in the appendix.

3.2. Study area and data

3.2.1. Forested watersheds in southeastern US

Our study area covers the southeast United States, defined by 13 southeastern states: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. This region includes approximately 1746 upstream water intakes in 1361 Public Water Systems (U.S. EPA, 2017) and a diverse mix of land use patterns and ecological zones. Parts of the region have seen rapid population growth and urbanization in recent decades. The region accounted for 87 % of national population growth in 2023 (US Census Bureau, 2023a), with expectations that these trends will continue (U.S. FS, 2023).

One element that distinguishes the Southeast from other parts of the country is its history of land use change on working agricultural and forest land, driven in some part by ownership patterns, which differ in the eastern and western parts of the U.S. In the Southeast, 90 % of the total forest area is owned and managed by families, corporations, other private entities, and some state and local governments. (Liu et al., 2021; Hewes et al., 2017). Due to private ownership, forests are at higher risk for conversion to development, agriculture, or other uses as detailed in future land use projections such as Liu et al. (2021), U.S. EPA (2020), and U.S. FS (2023). Further, this region faces multiple stressors affecting both water availability and quality that exacerbate water management for public water supply systems, including population growth (Sun et al. (2008)) and land use change.

Further, hydrological and forest sciences have shown that forests contribute disproportionately to water supply relative to their land area (Liu et al., 2021). Liu et al. (2021) have demonstrated that while forested lands comprise 36 % of the land area in the US, they contribute 50 % of the total water yield, and 38 % of public water systems receive more than 50 % of their water supply from forests. Hence, the problem of forest loss becomes crucial not only to the forest managers but also to the water utility managers in these regions.

3.2.2. Data and challenges

We conducted a survey of 1300 utilities across 13 states in the southeastern United States in the year 2022–2023. Email requests were sent to any water utility in the study region whose contact information was available. The Excel-based survey instrument, based on a 2014 AWWA survey conducted by Warziniack et al. (2017), elicited the following information pertinent to this study.

- Median, minimum, and maximum water quality metrics (Turbidity, TOC, Total Coliform, TP, TN, and, TSS).
- Monthly averages of Turbidity and TOC in the most recent year.
- Details on the percentage and quantity of chemicals used in various treatment processes.
- Intake points and source of water (river/reservoir)
- Capital and chemical costs.

As surveys were limited to facilities (and associated contact emails) and those who responded did so as facility representatives, we did not offer reimbursement for participation. The resulting response rate was less than 5 % and the final data set contains 37 surveys (corresponding to 40 total intake points as some surveys provide information for multiple intakes); follow-up calls were made to request additional or missing information. While the survey response rate was relatively low, it was

similar to or better than other surveys of water utilities in the literature. For example, Warziniack et al. (2017) collected about 37 surveys throughout the US in a similar study published in 2017. Price and Heberling (2018) observe that most of the cross-sectional analyses linking water treatment costs, water quality, and land cover consist of less than 50 observations (Ernst et al., 2004; Freeman et al., 2008; Mosheim and Ribaudo, 2017; Oklahoma Water Resources Board, 2011b; Renzetti, 2001; Warziniack et al., 2017). Our resulting sample is slightly biased toward mid-sized treatment plants. While the full sample of facilities includes many facilities servicing less than 5000 people (~25 %), less than 10 % of our survey responses included small facilities. Our large facilities (servicing more than 200,000) are around 8 % of our sample, while these larger facilities correspond to approximately 5 % of the facilities in the full sample.

Each of the public water system intake points were indexed to a National Hydrography Dataset (NHD) NHDPlus Version 2.1 catchment (Moore and Dewald, 2016) as described in Caldwell et al. (2023). This allowed us to quantify upstream land use from the 2019 National Land Cover Dataset (Wieczorek et al., 2018; Wickham et al., 2023) and watershed area for each intake location and allowed us to utilize modeled estimates of TN and TP from four regional US Geological Survey SPARROW water quality models that intersect with the South, including the Northeast (Ator, 2019), Southeast (Hoos and Roland II, 2019), Midwest (Robertson and Saad, 2019; Robertson and Saad, 2021), and Southwest (Wise et al., 2019). Caldwell et al. (2023) used this model to include both anthropogenic and natural factors while linking variability in water quality with land cover classes.

We include data on both the population served directly and the population served via purchasing from the public water system at the utility level from Liu et al. (2022). We aggregate population directly served and through purchases to estimate the total population served by each public water system. Finally, we use data from the USDA Forest Service RPA for future land use projections (2070 vs 2020) (U.S. FS, 2023).

The SSPs represent the range of populations, providing upper and lower bounds on projected land use and nutrient flow changes and a good robustness check. The survey instrument was designed with input from experts from water utilities and tested with a small sample for length of response time and burden on the utility. Ultimately the survey instrument sought to balance the need for detailed cost and engineering data with information tailored to specific variables highlighted in the literature as influential on water treatment costs.

3.2.3. Descriptive statistics and correlation

The descriptive statistics for the ecosystem service production function and the economic valuation are provided in Table 2. The table presents descriptive statistics showing relationships between the water quality and ecological variables (summarized at the water intake point) and survey responses, including chemical treatment costs (facility-level). We also include the variables used in computing the change in treatment costs under different future projections of land and population. We report a different number of observations for ecological variables at the water intake point as some facilities provided a single survey but with responses for multiple intake points. The Public Water System facility represents the individual unit for the economic valuation function, while results from the ecosystem service production function and related regressions presented in the supplement are summarized at the water intake point.

The largest land use category in our sample is forests, occupying a maximum of 89 % and a mean of 20.9 % across water utilities in our survey. Rangeland and Developed land are the next major land-use types with a mean of 18.79 % and 10.16 % and a maximum of 74.84 % and 47.74 %, respectively. Other land-use categories consist of mean and maximum of less than 50 % including crop.

Of particular note in Table 2 are the means associated with projected costs differences (% 2070 Cost Difference...). The distribution of costs

Table 2

Summary of water utility survey results and projections of population served, TN and TP concentration, and treatment cost changes by 2070 under the four future land use scenarios.

Statistic	N	Mean	St. Dev.	Min	Max	Units
Average daily production	36	7.53	10.239	0.059	40.62	MGD
Cost per unit production	36	1189.627	2382.271	44.506	11,486.67	\$
Median TOC	33	3.307	1.781	0.9	6.79	PPM
Median Turbidity	34	68.686	345.313	0.035	2022.0	NTU
pop served directly	37	34,143.46	67,603.66	0	277,080	Number
pop served via purchases	37	72,280.84	215,742.9	0	950,743	Number
total pop served	37	106,424.3	218,237.6	740	950,743	Number
CUM AREAKM2	40	3083.551	5093.97	2.788	21,908.37	Square kms
Barren	40	0.148	0.157	0.0	0.67	Percent
Crop	40	2.58	3.881	0.0	18.2	Percent
forest	40	53.689	20.89	9.87	89.02	Percent
developed	40	13.789	10.162	2.1	47.74	Percent
rangeland	40	27.343	18.793	3.91	74.84	Percent
tn conc mgL	40	0.992	0.421	0.13	2.325	mgL
tp conc mgL	40	0.146	0.194	0.004	1.156	mgL
Future Projections						
2020 Population	1359	54,653	182,246	90.0	306,287	Count
2070 Population under SSP3	1359	60,631	216,402	102.28	3,466,259	Count
2070 Population under SSP5	1359	110,211	388,203	189.98	6,259,342	Count
2020 MGD	1359	4.33	14.4	0.01	231.96	MGD
2070 MGD under SSP3	1359	4.8	17.18	0.01	274.05	MGD
2070 MGD under SSP5	1359	8.72	30.77	0.01	479.87	MGD
Calculated Values						
2020 Total Nitrogen (TN)	1359	1.13	0.56	0.42	3.67	mgL
2070 TN under HAD-SSP3	1359	1.11	0.53	0.42	3.49	mgL
2070 TN under HAD-SSP5	1359	1.12	0.53	0.42	3.48	mgL
2070 TN under MRI-SSP3	1359	1.12	0.54	0.42	3.45	mgL
2070 TN under MRI-SSP5	1359	1.13	0.54	0.42	3.44	mgL
2020 Total Phosphorus (TP)	1359	0.13	0.1	0.03	0.69	mgL
2070 TP under HAD-SSP3	1359	0.13	0.09	0.03	0.64	mgL
2070 TP under HAD-SSP5	1359	0.13	0.09	0.03	0.64	mgL
2070 TP under MRI-SSP3	1359	0.13	0.09	0.03	0.63	mgL
2070 TP under MRI-SSP5	1359	0.13	0.09	0.03	0.63	mgL
% 2070 Cost Diff TN under HAD-SSP3	1359	0.0	0.09	-0.23	1.74	Percent
% 2070 Cost Diff TN under MRI-SSP3	1359	0.01	0.1	-0.23	1.77	Percent
% 2070 Cost Diff TN under HAD-SSP5	1359	0.0	0.1	-0.26	1.9	Percent
% 2070 Cost Diff TN under MRI-SSP5	1359	0.01	0.11	-0.3	1.84	Percent
% 2070 Cost Diff TP under HAD-SSP3	1359	-0.01	0.06	-0.17	0.92	Percent
% 2070 Cost Diff TP under MRI-SSP3	1359	0.0	0.06	-0.17	0.93	Percent
% 2070 Cost Diff TP under HAD-SSP5	1359	0.0	0.06	-0.19	0.99	Percent
% 2070 Cost Diff TP under MRI-SSP5	1359	0.0	0.06	-0.23	0.96	Percent

changes across our 4 scenarios and 2 pollutants are centered around zero with long tails to the right (i.e. cost increases). The fairly small standard deviations indicate a relatively tight bunching of observations near the mean. Also of note, while there were 1361 facilities available in our data set, two were dropped due to missing population information.

Additional binary data from the survey are described in Table 3. Most of the public water systems in our data sample use conventional treatment (27) as opposed to advanced treatment (6). A little more than half of these facilities (i.e., 26) have intake points on rivers as opposed to in a reservoir. Warziniack et al. (2017) reported higher and more variable levels of turbidity for run-of-river intakes. This might explain larger values of summary statistics for turbidity in the data as well.

Table 3

Summary of binary variables collected in the water utility survey. The river variable response = 0 represents a water utility whose intake is on a reservoir while response = 1 indicates the intake is run-of-river.

Variable	N	Response = 0	Response = 1
Conventional Treatment	37	10	27
Advanced Treatment	37	31	6
River	40	26	14

4. Results

This section summarizes results from the economic valuation function and projected changes in cost with future land use conversions. Fig. 1 shows correlation plots of water quality variables and forest cover with unit costs based on survey responses. Consistent with previous work, TOC was significantly positively correlated with per unit treatment costs while turbidity was not significant, however, there is a wide variation across facilities in reported water quality and treatment costs. We see an insignificant but negative and highly variable relationship between forests and annual treatment costs. This highlights the complexity of understanding the dynamics of the relationship between forest cover and unit costs similar to the observation in Warziniack et al. (2017).

4.1. Results from ecological-economic functions

Table 4 describes the results from the economic valuation function using the survey-reported water quality variables. Three different model specifications were employed for robustness checks. These models differ in terms of the independent variables included in each model: (1) includes only the high population density variable (referred to as “urban”) variable, i.e. the variable created based on population served from the

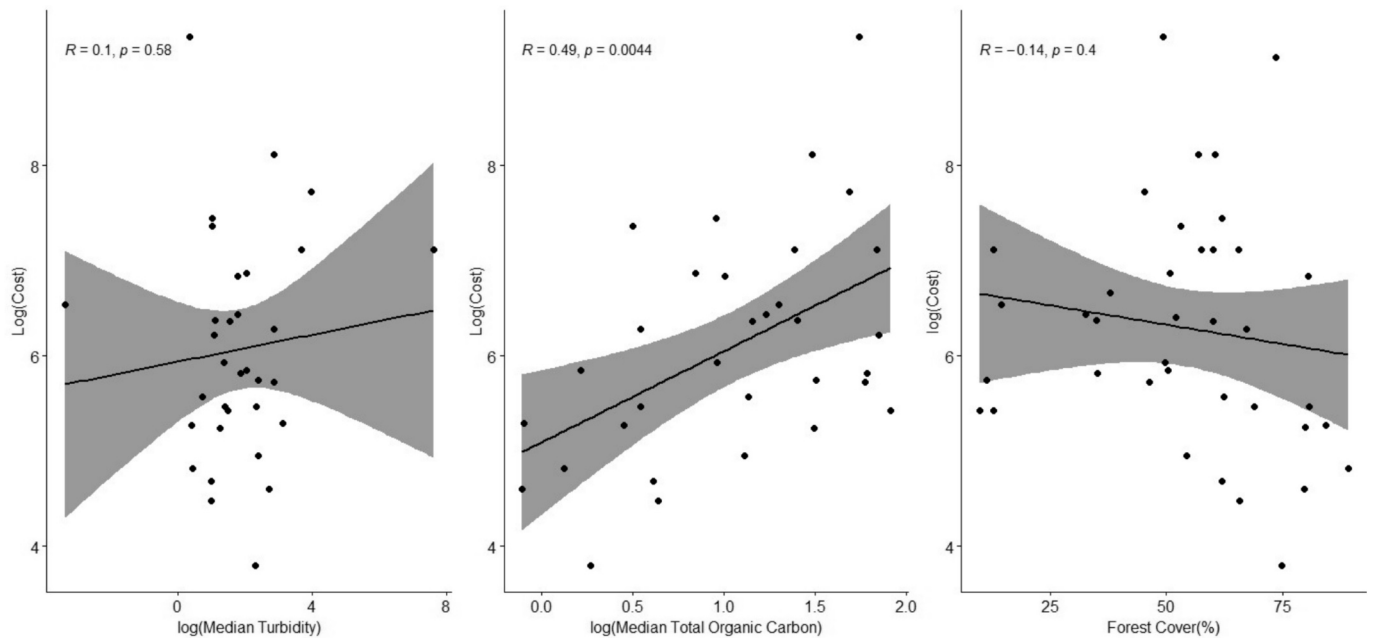


Fig. 1. From left to right, correlation between Log (Costs) and Median Turbidity ($R = 0.1$, $p = 0.58$), Median Total Organic Carbon ($R = 0.49$, $p = 0.0044$), and Forest Cover Percent ($R = -0.14$, $p = 0.4$).

USEPA SDWIS, (2) includes all explanatory variables in the study, and (3) includes all explanatory variables along with an interaction variable between urban and average daily production. The incorporation of urban and average daily production variables helps test for scale efficiencies in treatment costs for larger facilities. For empirical estimation, we log-transform our dependent variable: annual chemical costs per unit of production, along with average daily production and population.² We observe a positive relationship between water quality variables reported in the survey responses, i.e., turbidity and TOC with unit costs. TOC and turbidity have positive effects throughout all the models, with TOC having a significant impact. The coefficients show that costs increase by 0.046 % and 0.951 % with a 1 % increase in turbidity and a 1 % increase in TOC, respectively, in specification 1, where all variables except the interaction variables are included. These coefficients change to 0.091 % and 1.041 % in Specification 2, where we include only the 'High population density' variable. Finally, we observe that when we control for all the variables including the interaction term, the costs change by 0.084 % and 1.144 % with a 1 % change in turbidity and a 1 % change in TOC. Since the variation in magnitude of these coefficients across the three specifications is minimal and the signs remain the same, we can conclude that the model is robust.³

The size of the treatment plant, indicated by the average daily production of water at the treatment plant has a positive relationship with the unit costs. Warziniack et al. (2017) found a negative relationship between the size of their treatment plant and the average daily production of water. However, the size of the treatment plant in their data set has a mean water production of 1100 MGD as opposed to 40.62 MGD in our sample. We also observe a positive relationship between the variable High Population Density (defined as PWS serving a population

greater than 5000) and the unit costs in the first two model specifications. However, in model 3, the variable High Population Density takes a negative value when we include an interaction term between urban and average daily production (i.e.) the size of the treatment plant. This indicates that the unit costs are reduced when treatment plants serve a higher population given the size of the treatment plants in our data sample.

Table 4

Coefficient values (standard error) and fit statistics for three regression model forms used to estimate drinking water treatment costs based on information collected in the water utility survey.

	Dependent Variable:		
	lCost		
	(1)	(2)	(3)
lMedTurb	0.046 (0.116)	0.091 (0.130)	0.084 (0.128)
lMedTOC	0.951*** (0.324)	1.041*** (0.352)	1.144*** (0.355)
Conventional Treatment		-0.0003 (0.528)	-0.050 (0.520)
Urban	0.011 (0.794)	0.068 (0.842)	-1.346 (1.334)
Advanced Treatment		-0.736 (0.595)	-0.780 (0.587)
Average Daily Production		0.013 (0.021)	-6.207 (4.597)
Urban: Average Daily Production			6.221 (4.598)
Constant	5.004*** (0.897)	4.795*** (1.040)	6.150*** (1.431)
Observations	32	32	32
R ²	0.245	0.300	0.350
Adjusted R ²	0.164	0.132	0.160
Residual Std. Error	1.080 (df = 28)	1.100 (df = 25)	1.083 (df = 24)
F Statistic	3.022** (df = 3; 28)	1.785 (df = 6; 25)	1.843 (df = 7; 24)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

² One of the assumptions we make in the dummy variables: conventional and advanced treatment is that NA is treated equal to zero (i.e., conventional treatment). This has been done since only the utilities with these treatments have responded.

³ We include some more models with different set of controls in Section 10.1 and observe that the sign and magnitude of coefficients for Turbidity and TOC, i.e. the variables of interest do not change, which shows robustness in the models.

4.2. Economic valuation function based on simulated nutrient concentrations

Table 5 includes four model specifications: (1) and (3) describe regression results with nitrogen concentration excluding and including drainage area (log CUMAREAKM2), and (2) and (4) describe the same models with phosphorus concentration. The coefficient for the concentration of both nutrients is positive and significant in the case of nitrogen for both model specifications and for phosphorus for model (4). Our results show that a 1 % increase in nitrogen concentration leads to an increase in costs per unit of production by 0.76 % and 0.91 % in specifications (1) and (3), and a 1 % increase in phosphorus increases the unit costs by 0.37 % and 0.46 % in specifications (2) and (4). Another interesting result that we observe is a negative relationship between cumulative upstream catchment area and costs. This could be due to a dilution effect. Larger upstream area means a more stable water supply and possibly less variability in water quality.

We also present a logistic regression between land use and capital costs in the appendix to demonstrate the probability of a water system having higher or lower capital costs with land-use changes. Results of this supplemental analysis help support our hypothesis that forest land use improves water quality and reduces treatment costs, but more nuanced analysis and additional data are needed to explore the relationship between land use, water quality, and treatment technology choices at the water treatment plant (Price and Heberling, 2018). In our dataset, less than five water systems use advanced technologies, likely due to their small plant sizes, and hence, we lack variation in the technology choice for a more nuanced analysis of technology choice.

4.3. Cost changes and future LU changes

Fig. 2, created in Python using the Plotly package (Plotly Technologies Inc, 2015), presents a scatter plot and fitted curve presenting the relationship between simulated percentage changes in treatment costs

Table 5

Coefficient values (standard error) and fit statistics for four regression model forms used to estimate drinking water treatment costs based on information collected in the water utility survey and estimated nutrient concentrations at drinking water intake facilities.

	Dependent Variable:			
	lCost			
	(1)	(2)	(3)	(4)
ltn_conc_mgL	0.763* (0.396)		0.910** (0.405)	
ltp_conc_mgL		0.366 (0.222)		0.465* (0.230)
Urban	−1.128 (0.991)	−0.849 (0.995)	−1.476 (1.009)	−1.152 (1.005)
Average daily Production	0.109 (0.234)	0.105 (0.238)	0.190 (0.238)	0.191 (0.242)
River	0.105 (0.406)	0.035 (0.422)	0.173 (0.404)	0.080 (0.417)
Log_CUMAREAKM2			−0.144 (0.103)	−0.148 (0.106)
Urban: Average daily Production	−0.310 (0.269)	−0.298 (0.272)	−0.264 (0.267)	−0.252 (0.271)
Constant	7.595*** (1.001)	8.140*** (1.143)	8.696*** (1.266)	9.453*** (1.467)
Observations	39	39	39	39
R ²	0.207	0.185	0.252	0.232
Adjusted R ²	0.087	0.062	0.112	0.088
Residual Std. Error	1.184 (df = 33)	1.200 (df = 33)	1.167 (df = 32)	1.183 (df = 32)
F Statistic	1.724 (df = 5; 33)	1.500 (df = 5; 33)	1.799 (df = 6; 32)	1.613 (df = 6; 32)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

(y-axis) and forest loss in areas upstream of each facility under the future land use scenarios (x-axis), using the TN cost model. Scatter plots show a strong and positive correlation between forest loss and projected water treatment cost changes, with a consistent slope across all future scenarios. The results imply that a 1 % change in forest loss in an upstream watershed results in a roughly 1.7 % increase in treatment costs. Conversely, gains in forest area result in projected reductions in treatment costs for some facilities. The results appear to be robust across the four scenarios used, with coefficients ranging between −1.7344 and −1.7142.

Similar results occur for the TP model (Fig. 7 in the supplement). For TP, a 1 % loss of upstream forest cover increases treatment costs by roughly 1 %. The notable difference is that the benefit of increasing upstream forest cover is lower by about 0.7 percentage points. Results are consistent across future scenarios, with coefficients ranging from −1.0169 to −0.9877.

Further, results indicate higher cost impacts for rural water treatment facilities due to higher projected rates of forest loss, with most of the facilities at the high end of the projected cost increase range falling in rural settings. However, there is a tight clustering around the axis, with facilities seeing both marginal forest losses and associated cost changes.

−0.9569).

The distribution of cost changes is similar across the various climate scenarios and socioeconomic pathway combinations. Fig. 3 plots the number of facilities against their projected cost changes in the TN model. The bulk of facilities are projected to experience between a 5 % decrease in costs (550 ≈ 41 % in MRI SSP5 to 618 ≈ 45 % in HAD SSP3) and a 5 % increase (409 ≈ 30 % in HAD SSP5 to 427 ≈ 35 % in MRI SSP3). Projected cost changes tend to be higher under the MRI SSP5 scenario, reflecting assumptions of high economic growth in that scenario.

Similar patterns are observed in the TP model (Fig. 7 in the appendix), though the shifts in costs by future scenario are not as consistent. Interestingly, under MRI SSP5, treatment costs associated with TP tend to fall compared to the MRI SSP3 scenario. Granted, the bulk of this shift lies within the peak of the distribution between a 5 % increase and a 5 % decrease in treatment costs.

4.3.1. Geographic distribution of projected cost changes

We create two maps using GeoPandas, Pandas, and Plotly in Python, for both TN and TP estimates of future change in cost under all four scenarios (see the supplemental appendix for TP) (Jordahl, 2020; Pandas Development Team, 2020; Plotly Technologies Inc, 2015). We visualize the results of our scenario analysis to project cost changes under future socioeconomic and climate scenarios by mapping the location of our study facilities and their change in treatment costs (both TN and TP) across the four scenarios. To aid in readability, we map the distribution of facilities where costs increase separately from those where it decreases. The first map (Fig. 4) includes facilities projected to have an increase in costs, while the second map (Fig. 5) includes facilities projected to have decreased costs under future land and population projections, both using the TN model. For illustrative purposes, Figs. 4 and 5 display cost changes under a scenario with high levels of socioeconomic development and warming (HadGEM2-ES, SSP5). Maps show the spatial heterogeneity in projected cost impacts across the southern region, driven by variations in long-term population growth and projected land use changes (including forest loss). In general, projected cost increases are clustered around urban areas with expected long-term development pressures (e.g., the greater Atlanta area, coastal South and North Carolina, and the mid-Atlantic coastal region). Other water utilities see declining costs, driven by projected loss of agricultural land for urban development and/or increases in forest land use. Agricultural land produces higher relative levels of nitrogen and phosphorus runoff than urban and other land uses due to fertilizer application and other management practices (Caldwell et al., 2023). Notably, the geographic

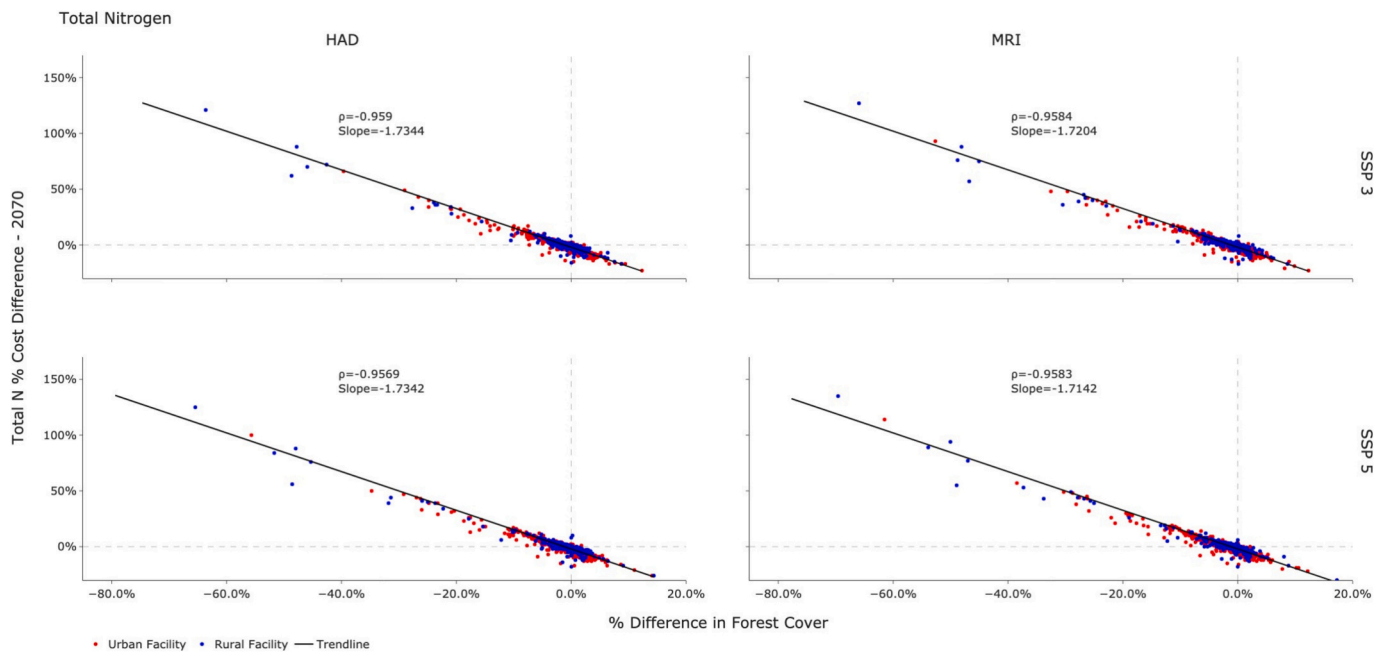


Fig. 2. Fitted relationship between projected forest cover change and estimated change in water treatment costs associated with Nitrogen. Red dots represent urban facilities, i.e. facilities serving high population density. The blue dots represent rural facilities serving less densely populated regions. Starting in the upper left and moving clockwise the scenarios pictured are: HAD-SSP3 ($\beta = -1.7344$, $\rho = -0.959$), MRI-SSP3 ($\beta = -1.7204$, $\rho = -0.9584$), MRI-SSP5 ($\beta = -1.7142$, $\rho = -0.9583$), HAD-SSP5 ($\beta = -1.7342$, $\rho = -0.9569$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

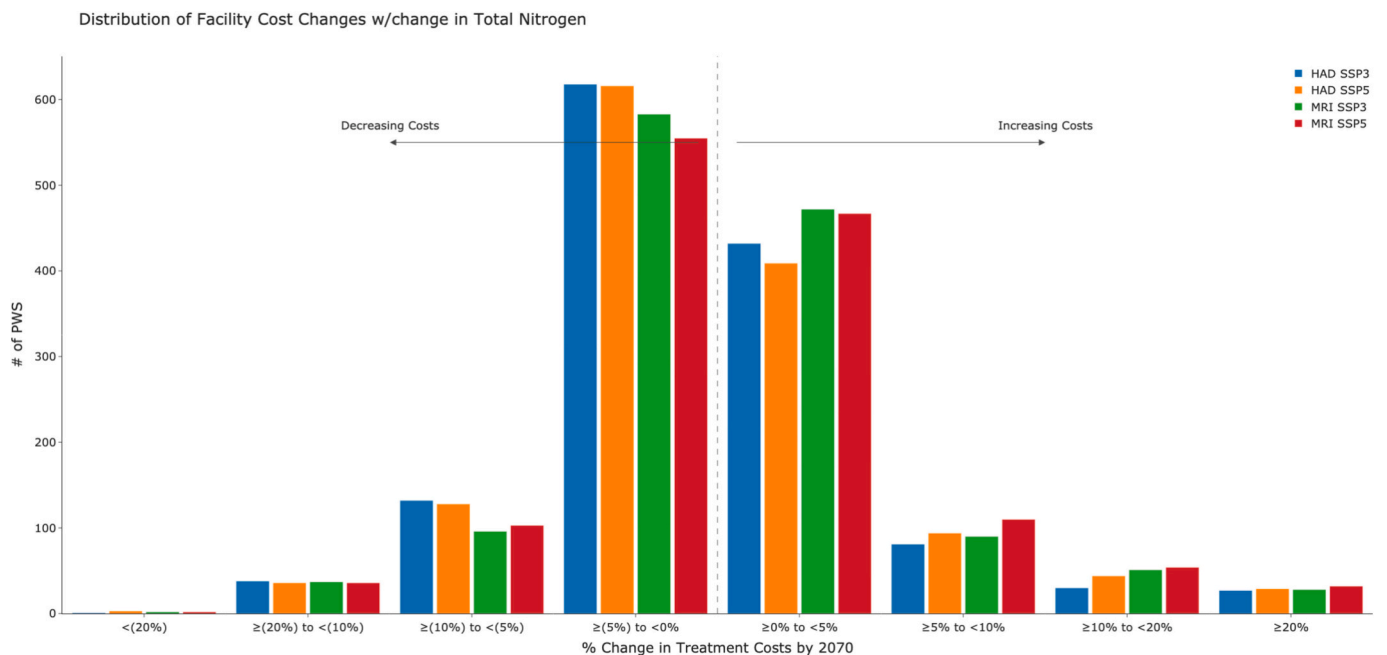


Fig. 3. Distribution of costs changes in the TN model across the 4 scenarios. Blue bars represent HAD-SSP3, orange bars HAD-SSP5, green bars MRI-SSP3, red bars MRI-SSP5. The majority of observations fall into a range of cost changes between -5% and $+5\%$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

distribution of results are quite homogeneous, however coastal Virginia and North Carolina tend to experience cost increases exclusively in our model. Perhaps pointing to the large watersheds that coalesce in these areas and their ability to transport nutrients. The existence of facilities in both Figs. 4 and 5 in the Mississippi River Delta indicates there is a greater degree of heterogeneity in the geographic distribution of treatment costs changes in that region.

The remaining scenarios and TP maps are available in Section 10.7 of

the appendix. Similar patterns exist across all scenarios evaluated in this study. The homogeneity of geographic distributions is present in both TN and TP maps and are robust to climate and socioeconomic assumptions. Naturally, there are pockets of differences between the two, namely the Virginia/North Carolina split discussed previously.

Results also show a large number of facilities (more than half) with projected cost changes of $\pm 2.5\%$. These facilities correspond to relatively small areas of projected land use changes (limited future devel-

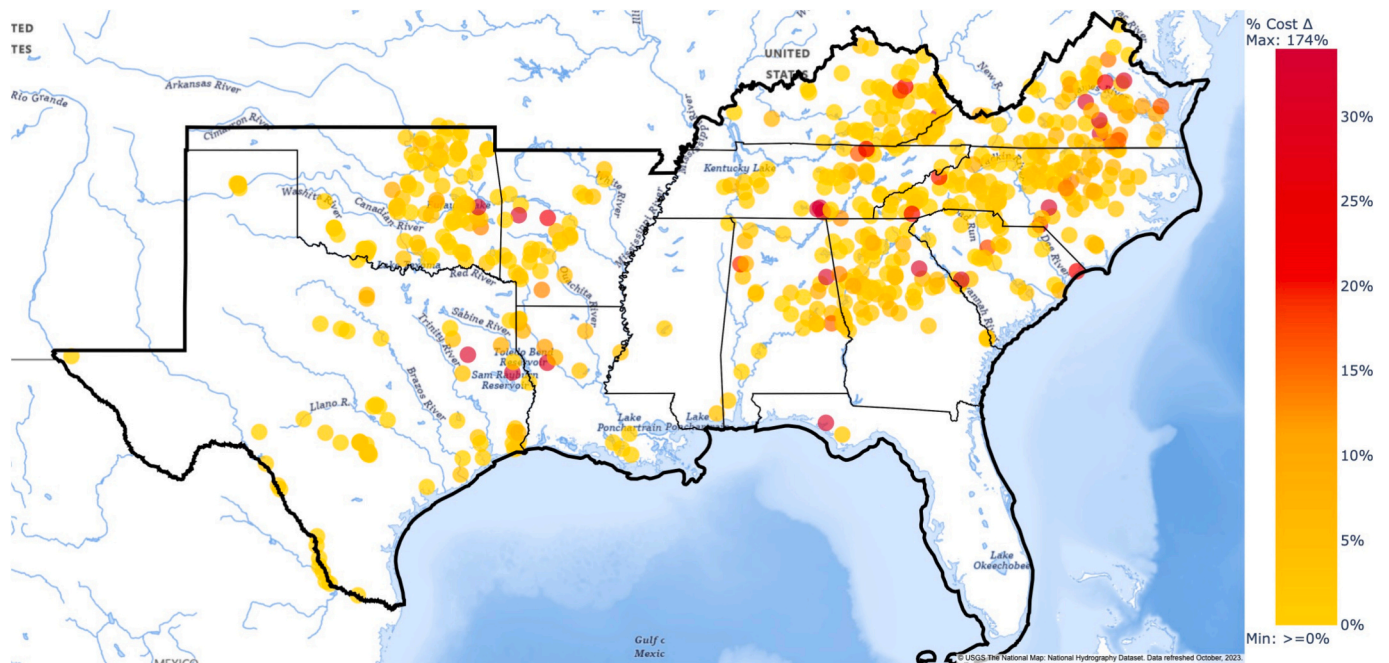


Fig. 4. Map of facilities with projected cost increases across the study region under the HAD SSP5 scenario using the TN model. Brighter red dots represent larger increases in costs, while more yellow dots represent closer to 0 % cost change. The max cost change in the results is 174 %. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

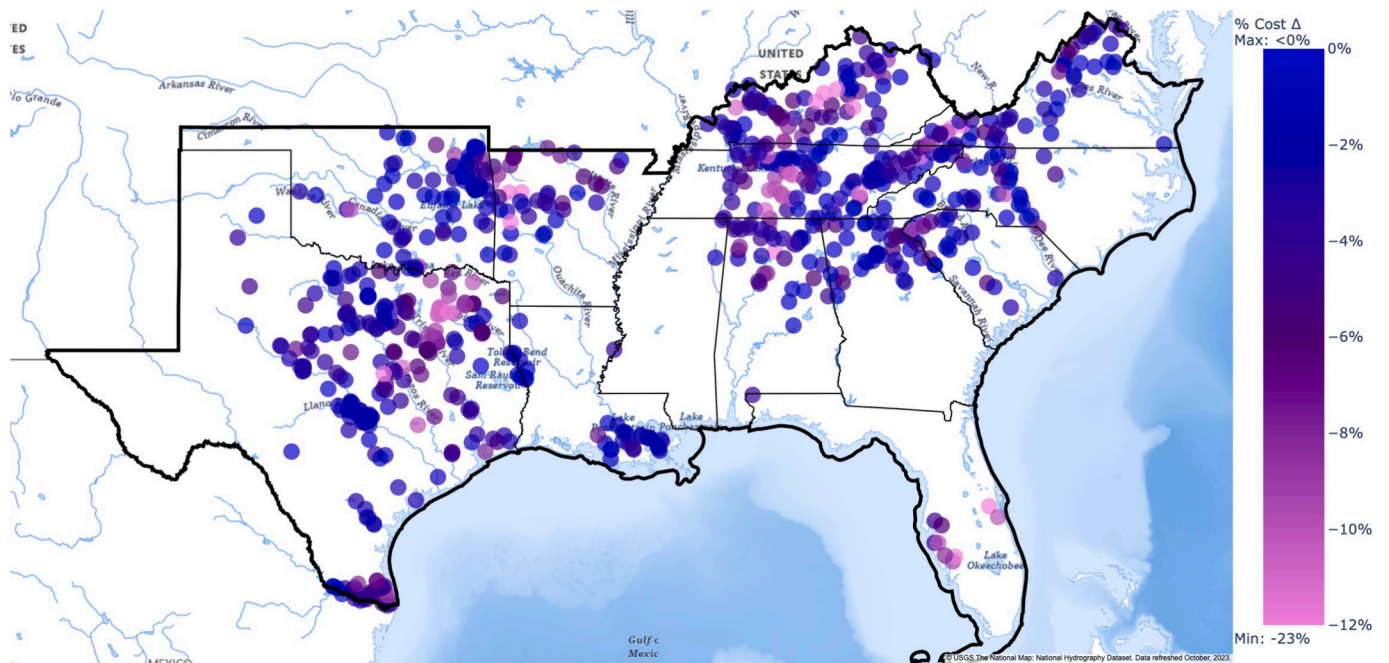


Fig. 5. Map of facilities with projected cost decreases across the study region under the HAD SSP5 scenario using the TN model. Brighter purple dots represent larger decreases in costs, while brighter blue dots represent closer to 0 % cost change. The max cost change in the results is -23 %. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

opment pressures) or the offsetting effects of future cropland and forest loss. More facilities see a 10 % greater reduction in water treatment costs from lower nutrient concentrations than facilities projected to see costs increase by more than 10 %.

On net, total projected regional cost changes are negative across the region, ranging from \$7–\$25 million yr^{-1} in cost savings, but with most of these savings occurring in areas with high relative levels of agricultural land conversion and reduced nutrients. Uncertainty results

provided in the appendix (Figs. 18–24) show confidence intervals in projected cost changes. Facilities are grouped according to their base (2020) treatment costs. We show narrow confidence intervals for mid-sized facilities but high uncertainty in our estimated cost impacts for very small and very large facilities.

4.3.2. Uncertainty analysis

While our sample size was in line with similar previous studies, we

conduct additional uncertainty analysis due to the limited number of observations to provide additional context for our results. Specifically, we conducted a bootstrapped sensitivity analysis. This supplemental analysis used the estimates and standard errors from the estimated cost models to bootstrap a distribution of estimated cost changes (additional details of which are in the Uncertainty Analysis Supplemental Index along with additional figures). At a high level, we binned together facilities with similar levels of percent cost change based on the model for each of the scenarios. Then we used the coefficient estimates and their standard errors to bootstrap 1000 versions of the model. Each facility is then modeled 1000 times.

Fig. 6 shows the results of this process for the nitrogen model and the HAD SSP 3 scenario, and other scenario results are available in the Uncertainty Analysis Supplement. The lefthand side is the distribution of facilities based on their percent cost change. Notably, a large number of facilities from the full sample see projected cost changes that fall within the -10% to $+10\%$ with a long tail to the right. This distribution aligns well with survey respondents, which also have projected cost impacts within the middle of the distribution ($\pm 10\%$) of projected cost changes.

The figure on the right plots the results from our bootstrapping procedure in the same bins. While there is a high degree of uncertainty in our predictions, this uncertainty tends to be smaller for the middle bins ($\pm 10\%$) and larger on the tails of the distribution (large negative or positive cost impacts) with fewer observations overall in these portions of the projected cost impact distribution., indicating better fit and lower uncertainty where the bulk of our predictions are made.

5. Discussion and conclusions

In this analysis, we show that the loss of forest cover could result in increases in marginal water treatment costs across many facilities in the southeastern U.S. The findings from surveyed utilities suggest that costs could increase by $0.046\text{--}0.091\%$ with a 1% increase in Turbidity and $0.951\text{--}1.144\%$ with a 1% increase in TOC. These results are consistent with the limited literature on the water-quality-treatment cost

relationship. Dearmont et al. (1998), Forster et al. (1987), Forster and Murray (2007), Heberling et al. (2015), Holmes (1988), Moore and McCarl (1987), and Mosheim (2006) demonstrate a positive and significant relationship between treatment cost and turbidity with coefficients ranging from 0.02 to 0.30% (Price and Heberling, 2018). Freeman et al. (2008) and Warziniack et al. (2017) found a significant and positive increase in treatment costs with 0.77% and 0.46% as the coefficients when there is a 1% increase in TOC. Few studies like Heberling et al. (2015) and Oklahoma Water Resources Board (2011a) found a positive but insignificant increase in treatment costs by 0.55% and 0.1% with a 1% increase in TOC. Other studies have estimated the relationship between TOC and chemical costs, but this relationship warrants further research with larger datasets. The results for turbidity can be interpreted in a more straightforward manner since the coefficients are in a similar range as the previous literature. However, there are less than 20 studies on cost-water quality relationships and hence, there is a need for much deeper research with substantial data collection efforts for treatment costs. Our economic valuation function for simulated nutrient concentrations shows a 0.763% and 0.91% increase in treatment costs with a 1% increase in TN concentration and a 0.366% and 0.465% increase in treatment costs with a 1% increase in TP concentration. We find only three papers in the literature that have investigated links between costs and nutrients like nitrogen and phosphorus. Mosheim and Ribaudo (2017) find a significant and positive cost increase of 0.06% with a 1% increase in nitrogen abatement. The study mentions that smaller water systems have a higher cost of nitrogen abatement. This finding is relevant to our estimates since the public water systems in the study are typically small (40.62 MGD is the highest average production). McDonald and Shemie (2014) and Heberling et al. (2015) investigated links between phosphorus and treatment costs, finding positive but insignificant coefficients of 0.19 and 0.02 , respectively, similar to the limited significance of the phosphorus variable in our valuation functions.

Moreover, our results support the notion that water quality benefits for reducing drinking water treatment costs are one of the many ecosystem services that forests provide. There are other economic benefits generated by good water quality, in terms of recreation and aquatic

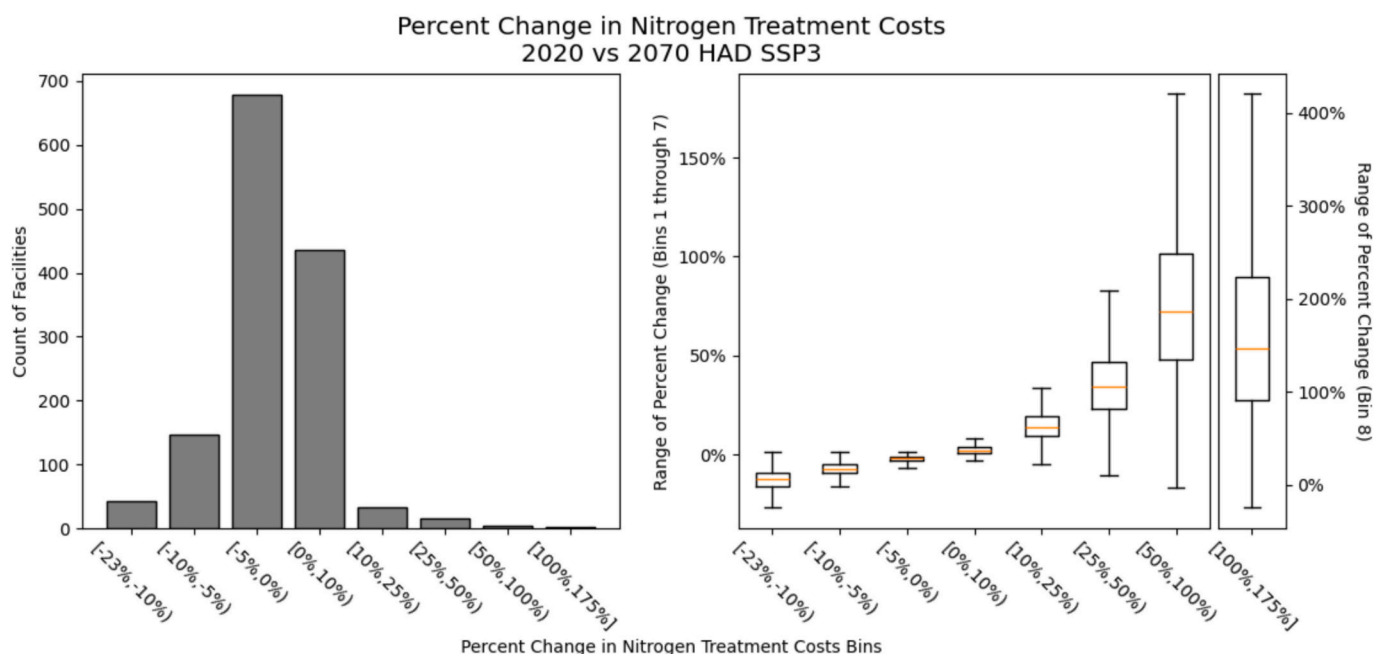


Fig. 6. Left: Distribution of facilities based on the predicted percent change in nitrogen costs under the HAD SSP 3 conditions. Note, [in a bin name denotes inclusive) denotes not inclusive. So, the first bin is $\geq -23\%$ and $< -10\%$. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios (i.e. MRI SSP 5). The rightmost bin (bin 8) is separated out from the others to allow for a separate scaling on the y-axis. It tends to be the most uncertain.

habitat protection. For example, we did not include opportunity costs of avoiding land uses with economic values of, for instance, development and food production. These are just some of many considerations in land use decisions, albeit, significant and complicated to calculate. Our nutrient function estimates contribute to a very narrow strand of nutrient-cost linkage literature and demonstrate the way future research can compute such estimates. The primary contribution of this analysis is that we link an ecological production function that uses water quality parameters most commonly estimated with hydrologic models with survey-based economic valuation to quantify the potential water treatment cost impacts of land use change.

Results from this study provide key information on the potential economic value of forest preservation for water quality maintenance. Results can also support broader forest ecosystem service assessments, integrated modeling, policy analysis, and natural capital accounting. Avoided water treatment costs would provide a key element when calculating the economic value of forests for either a value assessment of forests or natural capital accounting, given that forests form an important part of natural capital. Warziniack et al. (2023) included water treatment costs as indirect impacts of deforestation while computing natural capital accounts on forested lands.

Further, our results could help policymakers and water treatment plant managers prioritize near- and long-term interventions to maintain or increase the provision of water-related ecosystem services. Near-term, our results provide spatial hotspots for areas at risk of land use change in the coming decades, including urban-rural fringes. Our results can help prioritize the development of incentives to maintain existing forest area; for example, payments for water-related ecosystem services stacked with other ecosystem services such as carbon sequestration and timber values to reflect the myriad opportunity costs associated with forest loss, or benefits of forest expansion (Valatin et al., 2022). Longer-term, this analysis and related work support broader assessments of natural capital valuation to support policy design (Warziniack et al., 2025), or at a facility level, accounting for natural capital assets and co-benefits of water quality interventions such as forest protection in internal accounting protocols.

For example, Central Arkansas Water and the Eugene Water and Electric Board are two utilities that monitor and protect their respective water sources (Warziniack et al., 2017). These kinds of analyses would inform such efforts by supporting the ecosystem services valuation. Further, the treatment cost-water quality relationships and vulnerability to future land use change would facilitate the quantification of Source Water Protection (SWP) activities, which are currently viewed as an essential and cost-effective solution to provide safe drinking water (Price and Heberling, 2018). Price and Heberling (2018) note that whether the benefits from SWP activities exceed the cost is highly contextual, and the analysis presented in this study would assist in targeting areas where the benefits from these activities are higher. Thus, results from this analysis can also support broader forest ecosystem service assessments, integrated modeling, and policy analysis. Finally, the results highlight the importance of investment in programs such as “the *land and water coalition fund*” which focus on preservation of land and water by means of providing recreational ecosystem services (Vincent, 2010).

The uncertainty results serve as a validation of findings – that most water treatment facilities would likely see modest cost impacts (+/– 10 %) from future land use change driven by socioeconomic developments consistent with the illustrative RPA scenarios considered in this analysis, though there is uncertainty in subbasins that are expected to see rapid population growth and development, which could include loss of forests or agricultural lands, which could result in different directional changes in water quality. Focusing on the higher confidence, moderate impact range of outcomes (+/– 10 %), results of our uncertainty results also help to identify a subset of priority facilities for interventions (e.g., those with likely positive cost impacts), which could include investments in forest preservation. For example, using the nitrogen model and the same HAD SSP3 scenario again, we find 371 treatment facilities within the

projected cost impact range of 0–10 %, for a total of ~\$7 million per year in 2070 for this scenario and cost model specification. The average cost impact across these facilities is relatively small (~\$19,000 per year), but 29 of these facilities show a potential cost impact greater than \$50,000 per year and 14 facilities show a potential cost impact greater than \$100,000 per year using the deterministic model projections. These scenario results, including uncertainty ranges per facility, can help prioritize which facilities should be targeted for outreach and investment to avoid treatment cost impacts of potential future land use changes. However, these results also suggest that avoided drinking water treatment costs from forestland preservation may not be high enough to justify land preservation exclusively for source water quality protection in areas with high opportunity costs of land without considering other environmental and economic benefits provided by forests.

We offer methodological advancements through the linkage of economic valuation and ecological production functions in a large geographic region with high levels of private land tenure and development pressures. Our study is an important step to fill the data gaps of primary survey data in the water quality and water treatment space. As noted, utilities do not typically observe TN, TP, and TSS. Hence, combining primary data with ecological production functions (simulated data) can support analysis on the impact of land use change or other global change drivers on future water quality changes when there is a misalignment between environmental modeling tools (which focus on nutrients and total suspended solids) and water treatment facilities (which typically track TOC and turbidity).

There are some evident limitations in this analysis and opportunities for future research. First, the changes in climate used in the land use projections could also impact water quality through changes in streamflow processes and nutrient and sediment cycling. It was beyond the scope of this work to model the effect of climate on streamflow and water quality, thus our results here isolate the effects of land use change alone. Future studies could incorporate the effects of climate on water quality and treatment costs. Additionally, expanded data collection on the public water system characteristics is needed in order to further research and analysis in this area. Price and Heberling (2018) highlight the importance of targeted data collection efforts and the comparison of behavioral and engineering cost models. Data in cross-sectional studies linking water quality and costs have found data collection to be challenging, especially for water quality variables like nitrogen, phosphorus, algae, and cyanobacteria blooms.

This challenge is evident in this study, where we rely on a small sample size of water treatment plants in the Southeastern U.S. to extrapolate potential future water treatment cost changes under changes in land use and nutrient flows driven by global change factors. While our results offer insight into potential spatial differences in water treatment cost impacts of higher nutrient concentrations from LUC, our results may not capture local nuances of water treatment technologies and related factors that affect costs. In particular, our results may underrepresent smaller rural water treatment facilities, resulting in an average population served for each facility in our sample that is higher than the population mean. This outcome emphasizes the need for continued primary data collection at the facility-level for more refined cost estimates. More specifically, it highlights the need for increased outreach and recruitment of smaller treatment facilities to participate in future water treatment cost surveys.

Further, previous studies mention the unknown extent of the effect of source water quality or uncertainty about future water quality. We include the simulated changes in nutrient concentrations in our study but acknowledge the uncertainties in future land use and water quality characteristics across large watersheds. We also acknowledge potential temporal heterogeneity in nutrient flow changes resulting from LUC, which we do not account for in this analysis. Future studies should incorporate a wider variety of water quality variables (such as pH and algae) at a public water system level and incorporate the long-run cost impacts relative to short-run costs to eliminate the underestimation of

the source water quality effects on treatment-related costs. Water quality indicators such as Total Coliform, TP, TN, harmful algal blooms etc. could be collected on utility level so as to analyze their impact on cost and also their relationship with the forest cover loss and associated changes in physical water quality variables at water intake points. Further, these water quality indicators and costs could be collected at the utility level for the entirety of the US, consistent with [Warziniack et al. \(2017\)](#), but including additional facilities. Finally, further research specifically quantifying the impact of agricultural, forest, and storm-water best management practices on water treatment costs could be highly beneficial for informing land managers.

CRediT authorship contribution statement

Arpita Nehra: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Justin S. Baker:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Peter V. Caldwell:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Katherine L. Martin:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Travis W. Warziniack:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Richard H. Manner:** Writing – review & editing, Writing – original draft, Formal analysis. **Christopher M. Mihaiar:** Writing – review & editing, Writing –

original draft, Conceptualization. **Gregory E. Frey:** Writing – review & editing, Writing – original draft, Conceptualization. **Jennifer K. Costanza:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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Appendix A. Appendix

A.1. Estimating TN and TP concentrations from land use data for future projections

We used the methods described in [Caldwell et al. \(2023\)](#) to estimate Total Nitrogen (TN) and Total Phosphorus (TP) concentrations as a function of upstream land use for each Public Water System intake for future projections of drinking water treatment costs. In this approach, we developed multiple regression models of observed log-transformed TN and TP concentrations with the proportion of upstream area in developed, agriculture, and other natural land cover across more than 600 water quality monitoring sites in the South. The model form was:

$$\text{Log}(Q_i) = b_0 + b_{dev} * \text{DEVELOPED} + b_{ag} * \text{AGRICULTURE} + b_{on} * \text{OTHERNAT} + e_i$$

Where Q_i is the water quality parameter (TN or TP concentration), DEVELOPED, AGRICULTURE, and OTHERNAT are the percentages of upstream developed, agriculture, and other natural land cover classes upstream, respectively, b_x are regression terms, and e_i is an error term. The β_0 term represents the water quality parameter concentration when all of upstream developed, agriculture, and other natural land cover classes are zero, i.e., the water quality parameter concentration with only forest upstream. b_x for the TN and TP models are shown in [Table 6](#). Note that all b_x were significant at $\alpha = 0.05$. Additional details on this modeling approach can be found in [Caldwell et al. \(2023\)](#).

Table 6

Coefficient values and fit statistics for multiple regression models relating long-transformed TN and TP concentration to upstream developed, agriculture, and other natural land cover types (adapted from [Caldwell et al., 2023](#)).

Water Quality Parameter	b_0	b_{dev}	b_{ag}	b_{on}	N sites	R^2
TN	−0.860	0.015	0.023	0.013	631	0.41
TP	−3.358	0.019	0.032	0.014	605	0.31

A.2. Statistical comparison of key metrics between full sample and surveyed facilities

Table 7

Statistical comparison of key metrics between full sample and surveyed facilities.

Surveyfacility = 0					
Variable	Observation	Mean	Std. dev.	Min	Max
Population	1326	53,938.18	182,546.1	0	3,062,287
Prodmgd	1326	4.301	14.507	0	231.965
Total Nitrogen	1326	1.134	0.568	0.423	3.671
surveyfacility = 1					
Variable	Observation	Mean	Std. dev.	Min	Max
Population	35	78,593.57	165,956.8	740	950,743

(continued on next page)

Table 7 (continued)

Surveyfacility = 0					
Variable	Observation	Mean	Std. dev.	Min	Max
Prodmgd	35	5.303	9.194	0.059	49.439
Total Nitrogen	35	0.987	0.383	0.437	2.061

A.3. Robustness checks for economic valuation function

Table 8

Results from the economic valuation function.

	Dependent Variable:								
	lCost								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average Daily Production	0.011 (0.020)	0.008 (0.020)	0.010 (0.019)	0.013 (0.021)					−6.207 (4.597)
Urban: Average Daily Production									6.221 (4.598)
lMedTurb	0.053 (0.118)	0.072 (0.127)	0.052 (0.116)	0.091 (0.130)	0.046 (0.116)	0.072 (0.125)	0.046 (0.114)	0.046 (0.116)	0.084 (0.128)
lMedTOC	0.960*** (0.329)	0.929** (0.337)	0.963*** (0.321)	1.041*** (0.352)	0.951*** (0.324)	0.910*** (0.329)	0.951*** (0.316)	0.951*** (0.324)	1.144*** (0.355)
Urban	−0.067 (0.817)			0.068 (0.842)	0.011 (0.794)			0.011 (0.794)	−1.346 (1.334)
Advanced Treatment				−0.736 (0.595)					−0.780 (0.587)
Conventional Treatment		0.200 (0.487)		−0.0003 (0.528)		0.247 (0.467)			−0.050 (0.520)
Constant	4.977*** (0.910)	4.783*** (0.570)	4.913*** (0.466)	4.795*** (1.040)	5.004*** (0.897)	4.831*** (0.551)	5.014*** (0.423)	5.004*** (0.897)	6.150*** (1.431)
Observations	32	32	32	32	32	32	32	32	32
R ²	0.253	0.257	0.253	0.300	0.245	0.252	0.245	0.245	0.350
Adjusted R ²	0.142	0.147	0.172	0.132	0.164	0.172	0.192	0.164	0.160
Residual Std. Error	1.094 (df = 27)	1.094 (df = 27)	1.074 (df = 28)	1.100 (df = 25)	1.080 (df = 28)	1.075 (df = 28)	1.061 (df = 29)	1.080 (df = 28)	1.083 (df = 24)
F Statistic	2.283* (df = 4; 27)	2.337* (df = 4; 27)	3.153** (df = 3; 28)	1.785 (df = 6; 25)	3.022** (df = 3; 28)	3.145** (df = 3; 28)	4.694** (df = 2; 29)	3.022** (df = 3; 28)	1.843 (df = 7; 24)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9

Results from cost function when constant is removed. We keep the original models as we prefer consistency and the significant nutrient effects.

	Dependent Variable:		
	lCost		
	(1)	(2)	(3)
lMedTurb	0.192 (0.162)	0.309* (0.161)	0.242 (0.159)
lMedTOC	1.781*** (0.411)	1.480*** (0.452)	1.202** (0.462)
Conventional Treatment		1.108* (0.627)	0.786 (0.629)
Urban	3.899*** (0.544)	3.295*** (0.625)	3.908*** (0.693)
Advanced Treatment		−0.705 (0.794)	−0.662 (0.764)
Average Daily Production		0.005 (0.027)	7.605* (4.283)
Urban: Average Daily Production			−7.599* (4.282)
Observations	32	32	32
R ²	0.944	0.954	0.960
Adjusted R ²	0.938	0.944	0.948
Residual Std. Error	1.542 (df = 29)	1.468 (df = 26)	1.411 (df = 25)
F Statistic	162.596*** (df = 3; 29)	90.737*** (df = 6; 26)	84.651*** (df = 7; 25)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 10

Results from the nutrient cost function when constant is removed. We keep the original models as we prefer consistency and the significant nutrient effects.

	Dependent Variable:			
	lCost			
	(1)	(2)	(3)	(4)
ltn_conc_mgL	0.159 (0.633)	0.034 (0.595)		
ltp_conc_mgL			−0.414 (0.302)	−0.361 (0.285)
Urban	6.084*** (0.459)	4.621*** (0.744)	5.032*** (0.870)	3.774*** (0.973)
river	1.106* (0.627)	0.658 (0.616)	1.193* (0.611)	0.743 (0.604)
log_CUMAREAKM2		0.301** (0.125)		0.289** (0.122)
log_AP	−1.270*** (0.241)	−1.019*** (0.248)	−1.144*** (0.252)	−0.920*** (0.254)
Urban:log_AP	1.044*** (0.329)	0.537 (0.373)	0.913*** (0.334)	0.443 (0.370)
Observations	39	39	39	39
R ²	0.921	0.933	0.925	0.936
Adjusted R ²	0.909	0.921	0.914	0.924
Residual Std. Error	1.932 (df = 34)	1.808 (df = 33)	1.882 (df = 34)	1.766 (df = 33)
F Statistic	79.236*** (df = 5; 34)	76.347*** (df = 6; 33)	83.817*** (df = 5; 34)	80.330*** (df = 6; 33)

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

A.4. Results from supplemental ecological production function

Warziniak et al. (2017) point out that the water source at the intake point also influences raw water quality. Typically, it is expected that water flowing through reservoirs will experience lower turbidity levels since they let the solids settle out and remove some of the sediment before the water enters the treatment plant. Hence, we set $RIVER_i$ as a binary variable where it takes the value 1 if the water is river and 0, otherwise. We use a multivariable regression model where water quality variables are log-transformed as shown below:

$\log(Q_i) = \beta_0 + \beta_{LANDUSE_i} + \delta_i RIVER_i + \varepsilon_i$ where β_0 is the intercept term, β_1 is the marginal effect of land use change on water quality, δ_i is the marginal effect of a river intake on the water quality, and ε_i is the error term.

Table 4 describes the results from the ecosystem services production function. We remove an outlier where a facility reported treating only 1 % water from one of its raw water sources. We specify two model specifications for two water quality variables, i.e., turbidity and total organic carbon: Columns (1) and (3) only include land-use variables, and columns (2) and (4) include a variable for intake point being a river in addition to land-use.

Table 11

Results from the ecosystem service production function.

	Dependent Variable:			
	lMedTurb		lMedTOC	
	(1)	(2)	(3)	(4)
developed	−0.008 (0.030)	0.019 (0.034)	0.015* (0.008)	0.016* (0.009)
rangeland	0.015 (0.017)	0.016 (0.017)	0.011** (0.005)	0.010** (0.005)
Crop	−0.145 (0.086)	−0.143* (0.082)	0.019 (0.023)	0.018 (0.023)
Barren	−0.466 (1.803)	−1.039 (1.782)	0.830 (0.491)	1.081** (0.490)
Water	−0.200 (0.131)	−0.062 (0.141)	0.055 (0.036)	0.028 (0.039)
river		1.415** (0.680)		−0.327 (0.194)
Total Population		−0.00000 (0.00000)		−0.00000 (0.00000)
Constant	2.559*** (0.807)	1.617* (0.889)	0.058 (0.226)	0.218 (0.245)
Observations	36	36	36	36
R ²	0.175	0.293	0.366	0.450
Adjusted R ²	0.038	0.116	0.257	0.307
Residual Std. Error	1.694 (df = 30)	1.624 (df = 28)	0.462 (df = 29)	0.446 (df = 27)
F Statistic	1.276 (df = 5; 30)	1.658 (df = 7; 28)	3.346** (df = 5; 29)	3.152** (df = 7; 27)

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Typically, we find a positive relationship between total organic carbon (TOC) and forests. Converting 1 % forested watersheds to rangeland increases TOC by exp. (1.007)−1 = 0.011 %, 1 % of forested watersheds to developed land increases TOC by exp.(0.015)−1 = 0.015 % and 1 % of the forested watershed to barren land increases TOC by the highest percentage, i.e., 1.95 %. We also find that turbidity reduces with a 1 % conversion of the forested watershed to agricultural land and increases by 3.11 % when the intake point is a river.

We do not find any significant relationships between TOC and agricultural land. This is mainly because our sample data has a limited amount of

these areas. The mean amount of agricultural land is 2.58 % with the maximum being 18.2 %.

A.5. Results from the capital cost analysis

Price and Heberling (2018) remarked that the exclusion of capital expenditure underestimates the relationship between source water quality and treatment-related costs. Hence, we tease out the relationships between land use and capital costs. We set up our capital expenditures as a categorical variable with six categories: 0–10,000; 10,000–100,000; 100,000–1000,000; 1000,000–10,000,000; 10,000,000–100,000,000 and 100,000,000–1000,000,000.

We use an ordered logit model with the same variables as used in the ecosystem service production function. For the interpretation of results, we compute odds ratios from the ordered logit model. An odds ratio would reveal whether a particular event is more or less likely in a particular scenario over another. In this case, the odds ratio would reveal whether a 1 % increase in land use increases or reduces the probability that a treatment plant would face higher or lower capital costs. The results show that when there is a 1 % increase in the conversion of forests to developed areas, there is a $(1.152-1)*100 = 15.2$ % higher chance that the treatment plant will face higher capital costs. Further, we observe that the conversion of forests to other land uses also increases the probability of a water system facing higher capital expenditures, however, except conversion to a developed area none of comes out to be significant.

Table 12
Land-use and capital costs.

	Dependent variable:
	cap costs
developed	0.997 (0.038)
rangeland	1.012 (0.018)
Barren	17.039 (1.959)
Water	1.045 (0.170)
Crop	1.003 (0.081)
Urban	3.118 (1.119)
Observations	38
Note:	*p < 0.1; **p < 0.05; ***p < 0.01

A.6. Results from simulated suspended solid concentrations

Table 13
Results from the economic valuation function for total suspended solids.

	Dependent Variable:	
	lCost	
	(1)	(2)
lss_conc_mgL	0.093 (0.159)	0.145 (0.167)
High Population Density	−0.739 (1.052)	−0.902 (1.064)
river	0.197 (0.423)	0.256 (0.427)
log_CUMAREAKM2		−0.112 (0.111)
log_AP	0.037 (0.244)	0.085 (0.248)
High Density Population_log AP	−0.248 (0.280)	−0.204 (0.283)
Constant	6.692*** (1.352)	7.211*** (1.446)
Observations	39	39
R ²	0.127	0.154
Adjusted R ²	−0.005	−0.005
Residual Std. Error	1.242 (df = 33)	1.242 (df = 32)
F Statistic	0.960 (df = 5; 33)	0.970 (df = 6; 32)

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

A.7. Conceptual diagram illustrating the work flow of various modeling processing and data components that support the projections of potential future drinking water treatment costs under assumed land use change scenarios

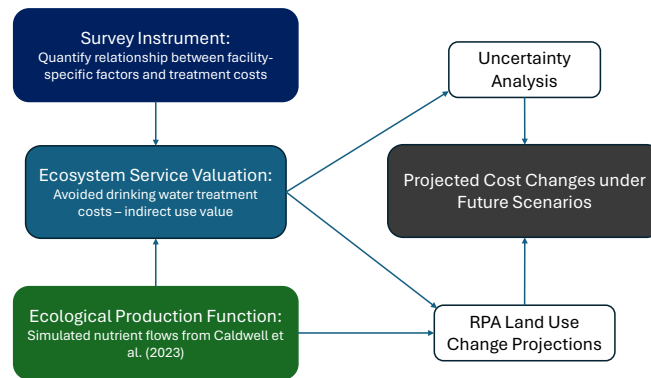


Fig. 7. Conceptual diagram illustrating the work flow of various modeling processing and data components that support the projections of potential future drinking water treatment costs under assumed land use change scenarios.

A.8. Supplemental cost change scatter plots using results from the phosphorus cost model

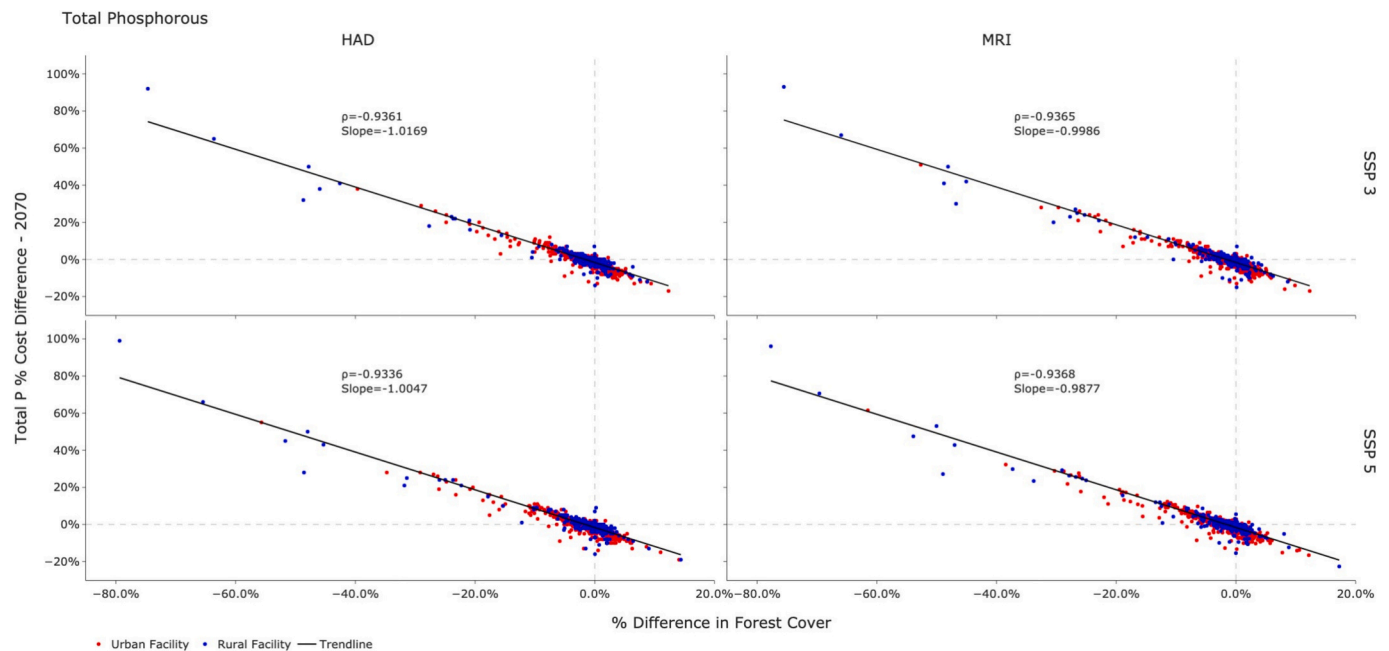


Fig. 8. Fitted relationship between projected forest cover change and estimated change in water treatment costs associated with Phosphorus. Red dots represent urban facilities, i.e. facilities serving high population density. The blue dots represent rural facilities serving less densely populated regions. Starting in the upper left and moving clockwise the scenarios pictured are: HAD-SSP3 ($\beta = -1.0169$, $\rho = -0.9361$), MRI-SSP3 ($\beta = -0.9986$, $\rho = -0.9365$), HAD-SSP5 ($\beta = -1.0047$, $\rho = -0.9336$), MRI-SSP5 ($\beta = -0.9877$, $\rho = -0.9368$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

($\beta = -0.9986$, $\rho = -0.9365$), MRI-SSP5 ($\beta = -0.9877$, $\rho = -0.9368$), HAD-SSP5 ($\beta = -1.0047$, $\rho = -0.9336$).

A.9. Supplemental cost change distributions using results from the phosphorus cost model

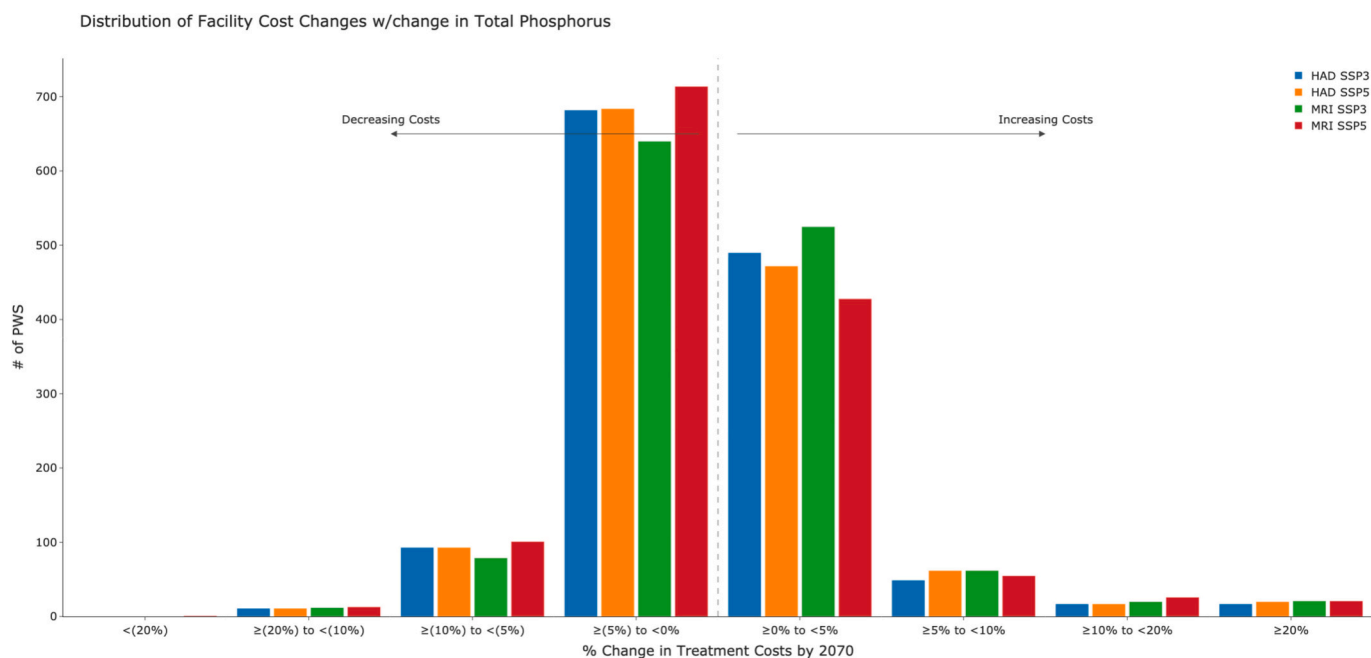


Fig. 9. Distribution of costs changes in the TP model across the 4 scenarios. Blue bars represent HAD-SSP3, orange bars HAD-SSP5, green bars MRI-SSP3, red bars MRI-SSP5. The majority of observations fall into a range of cost changes between -5% and $+5\%$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A.10. Supplemental maps of projected cost changes

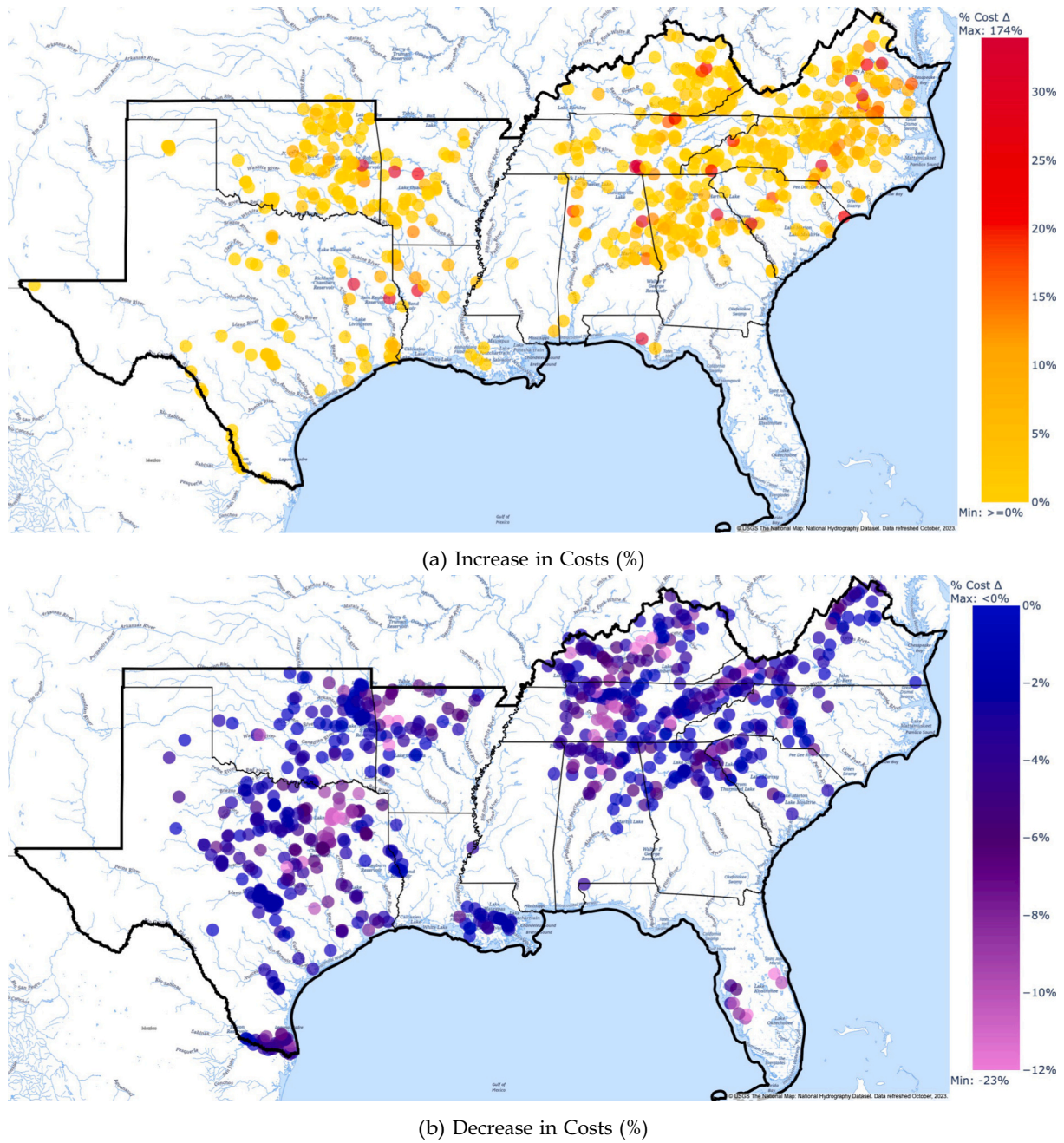
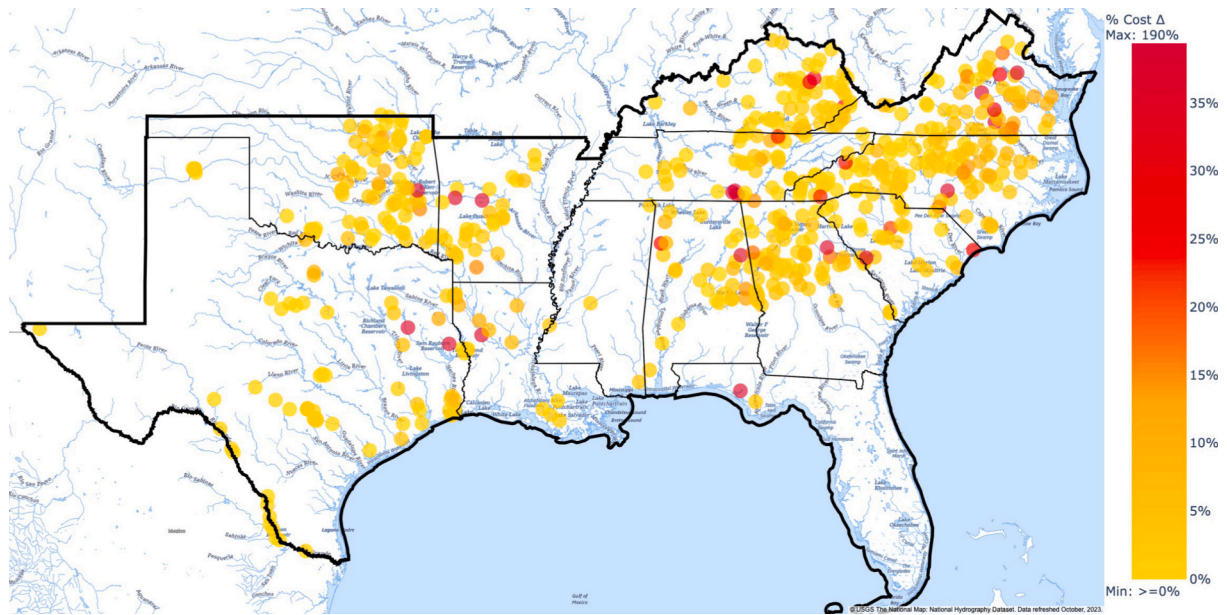
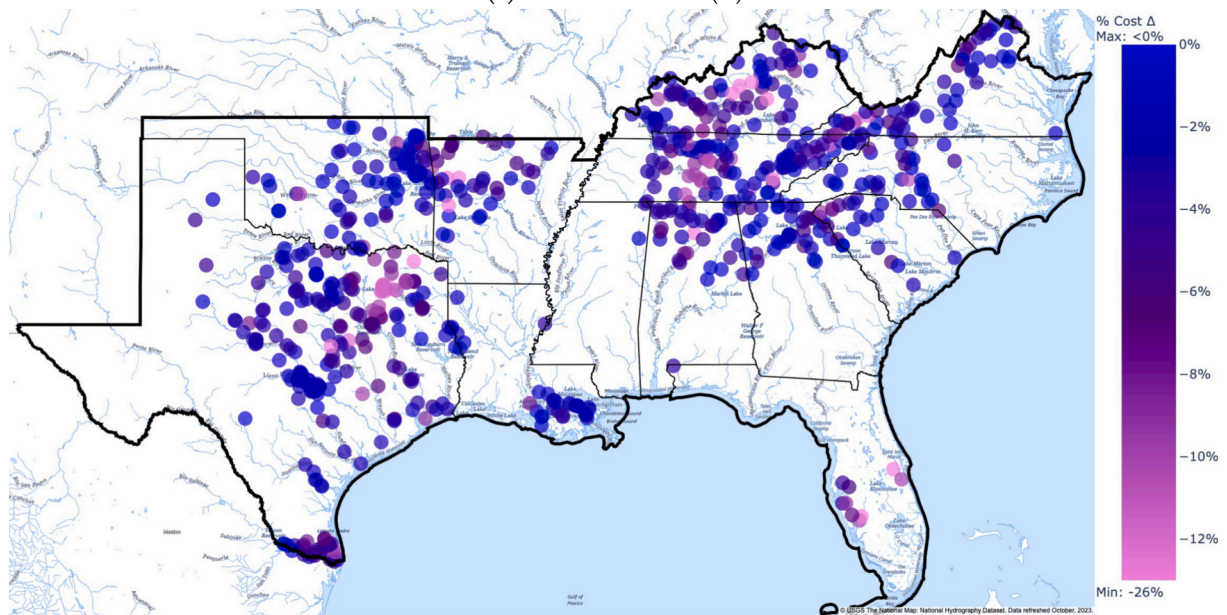


Fig. 10. Map of facilities' projected cost changes (%) with change in total Nitrogen across the study region under the HadCEM2-ES climate scenario and Socio-economic Pathway 3. Maximum percent change is 174 % and the minimum is -23 %.

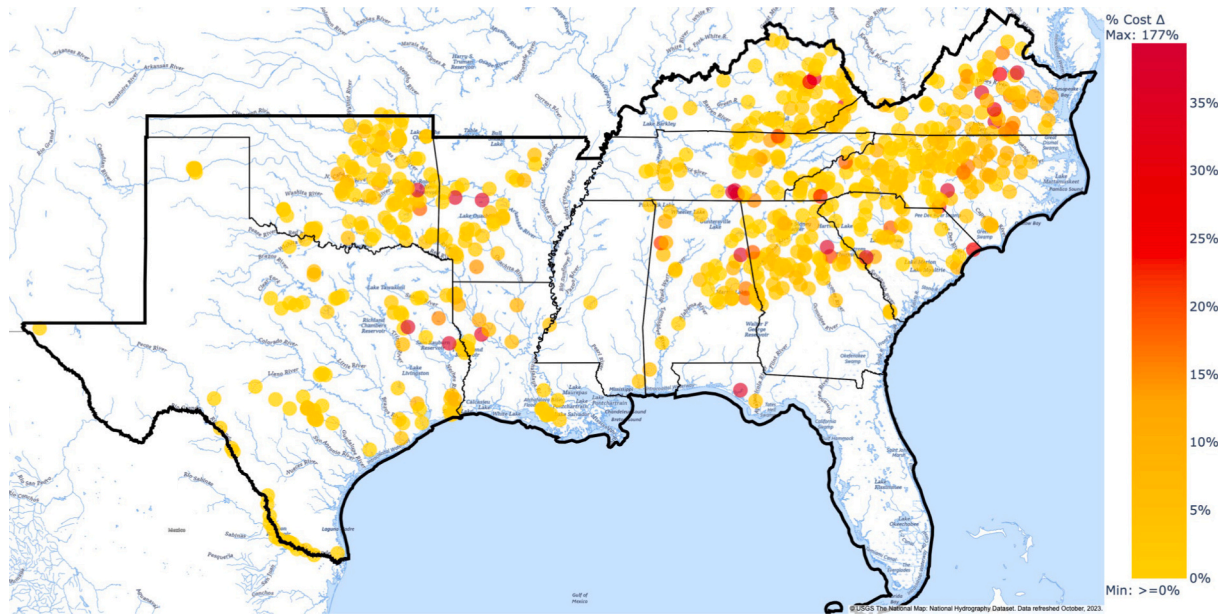


(a) Increase in Costs (%)

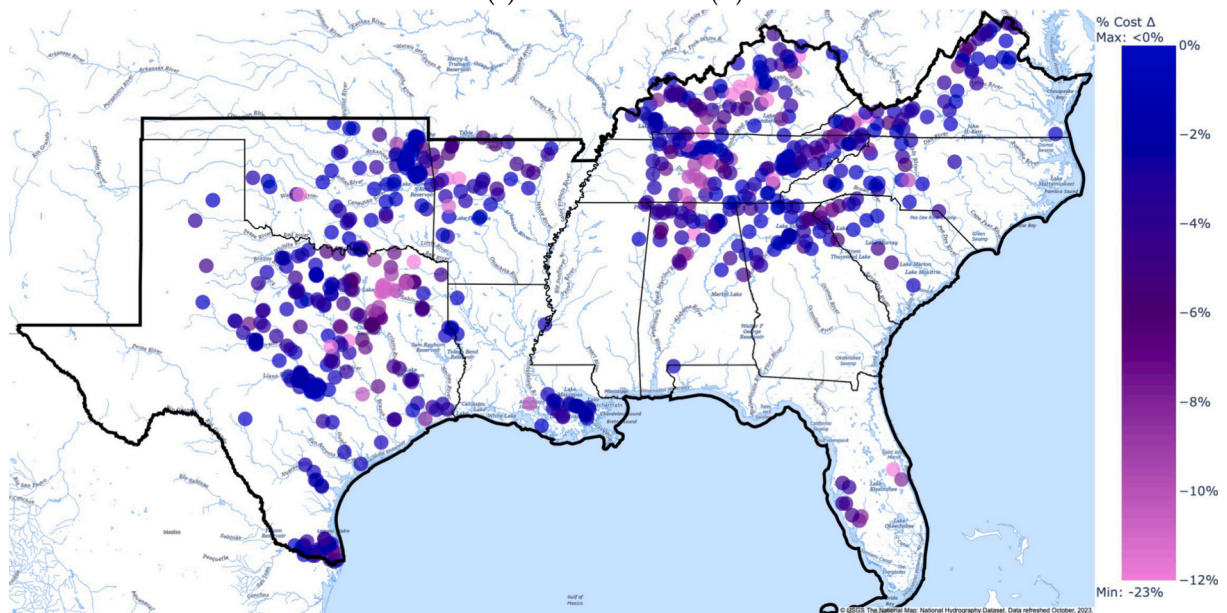


(b) Decrease in Costs (%)

Fig. 11. Map of facilities' projected cost changes (%) with change in total Nitrogen across the study region under the HadCEM2-ES climate scenario and Socio-economic Pathway 5. Maximum percent change is 190 % and the minimum is -26 %.

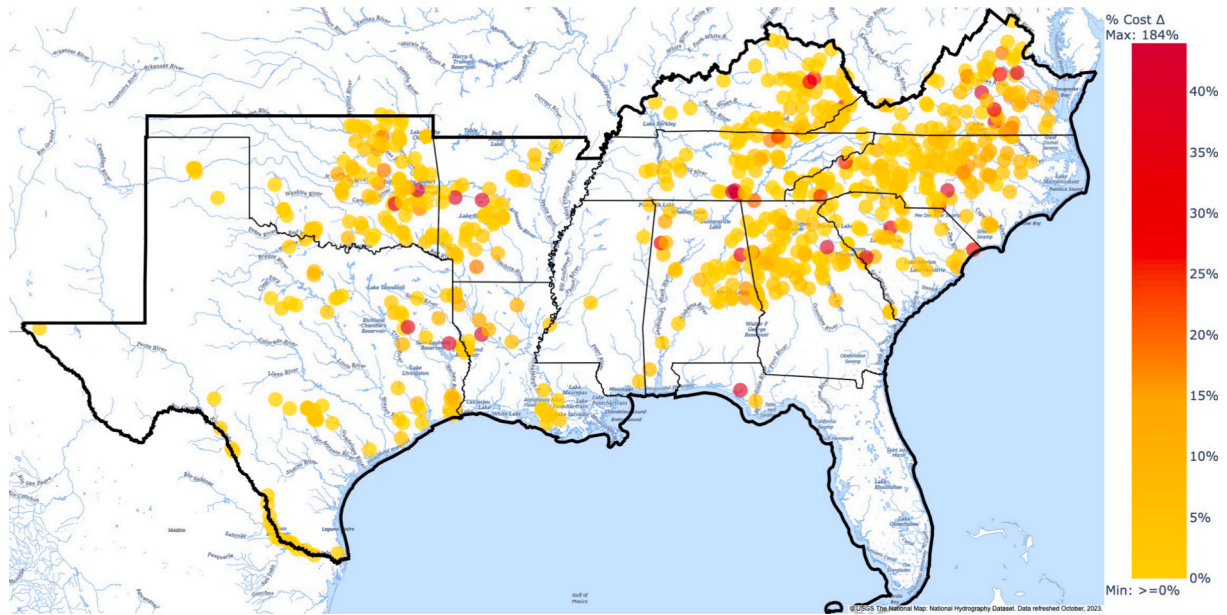


(a) Increase in Costs (%)

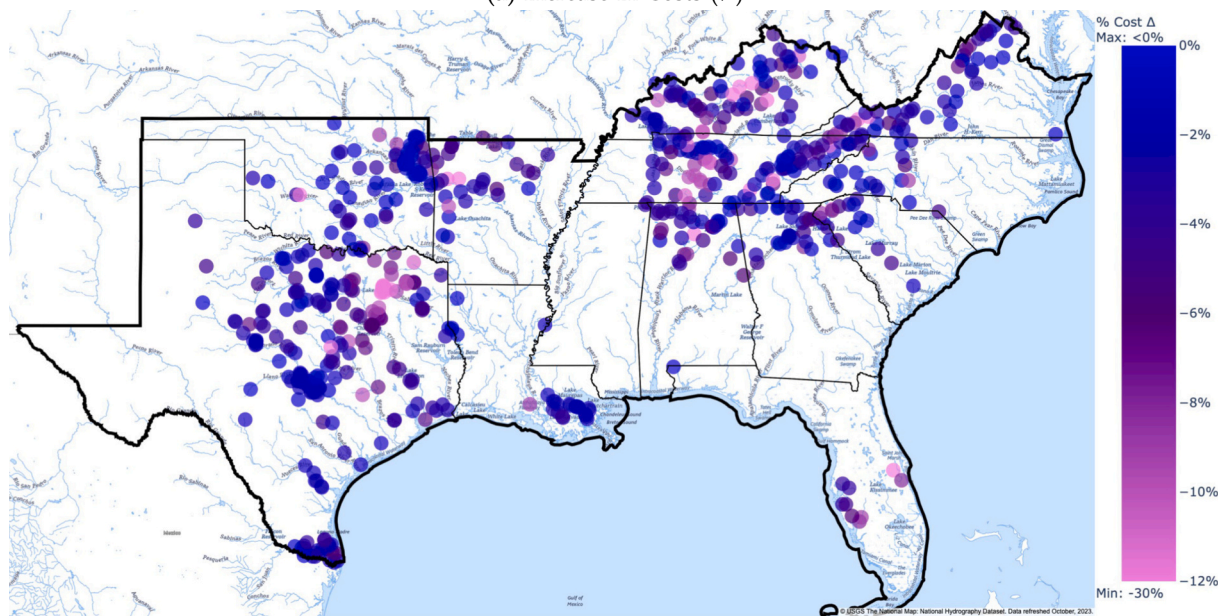


(b) Decrease in Costs (%)

Fig. 12. Map of facilities' projected cost changes (%) with change in total Nitrogen across the study region under the MRI-CGCM3 climate scenario and Socio-economic Pathway 3. Maximum percent change is 177 % and the minimum is -23 %.

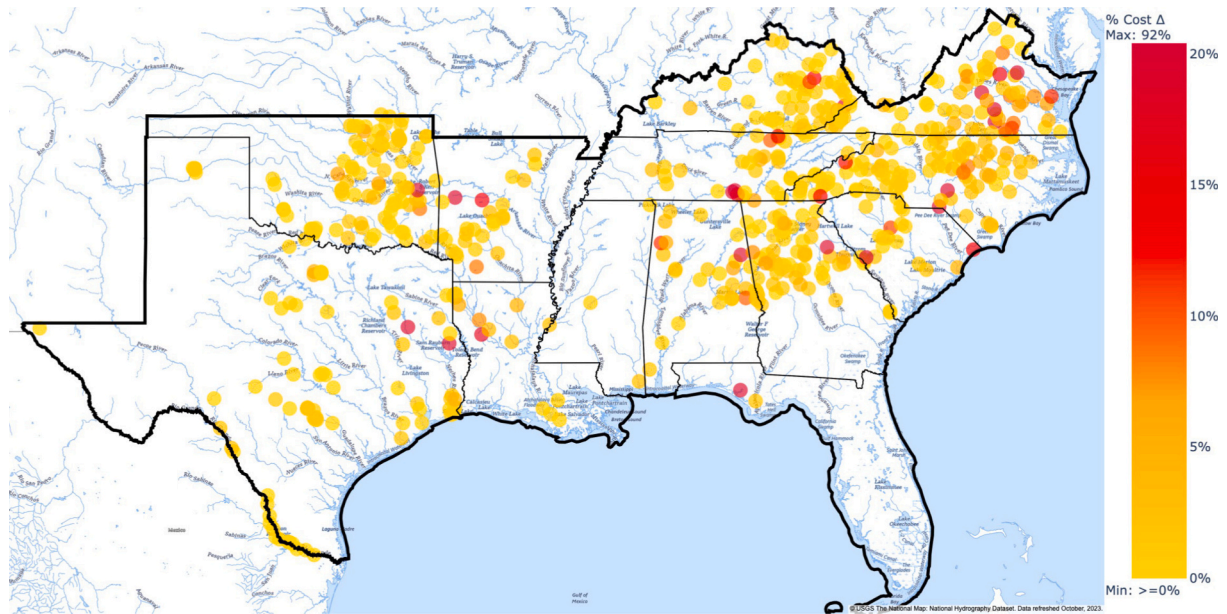


(a) Increase in Costs (%)

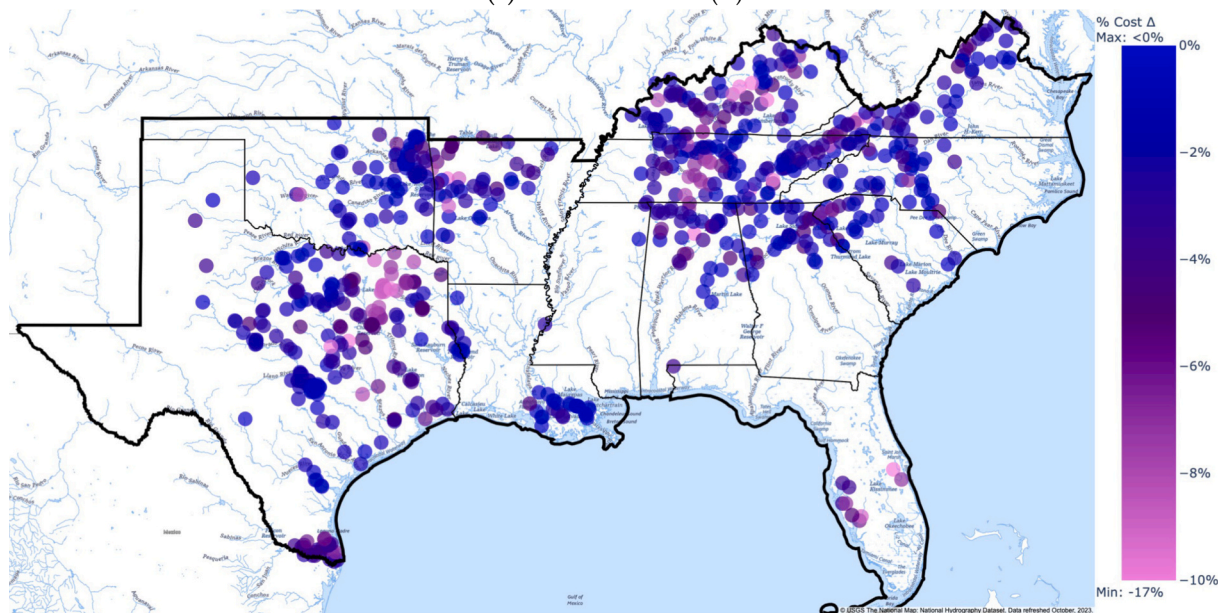


(b) Decrease in Costs (%)

Fig. 13. Map of facilities' projected cost changes (%) with change in total Nitrogen across the study region under the MRI-CGCM3 climate scenario and Socio-economic Pathway 5. Maximum percent change is 184 % and the minimum is -30 %.

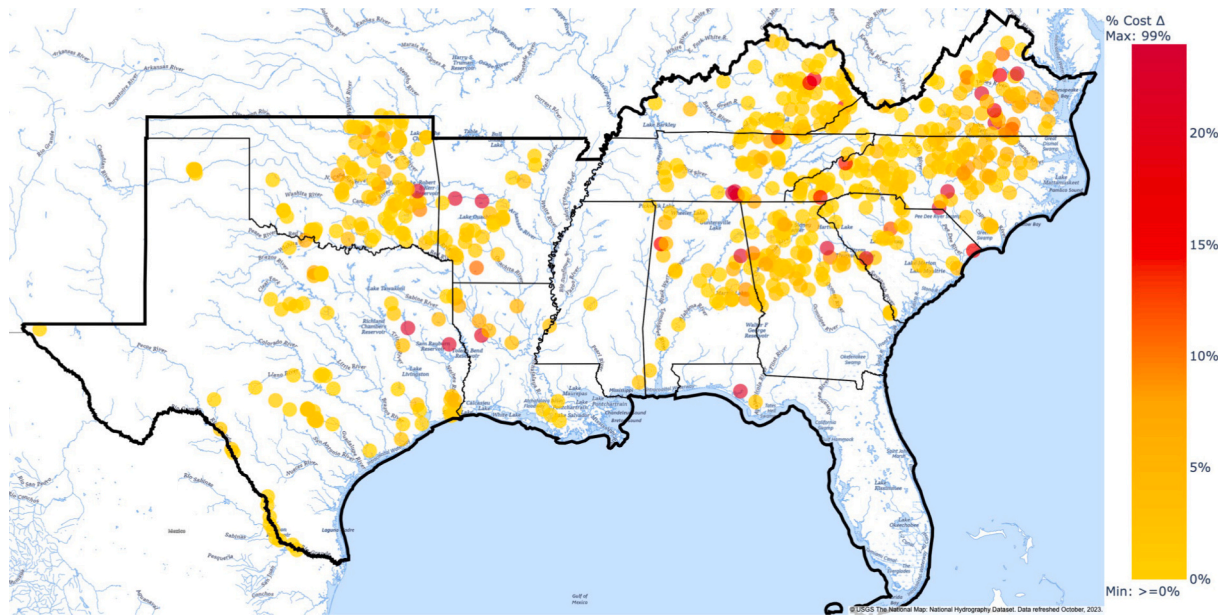


(a) Increase in Costs (%)

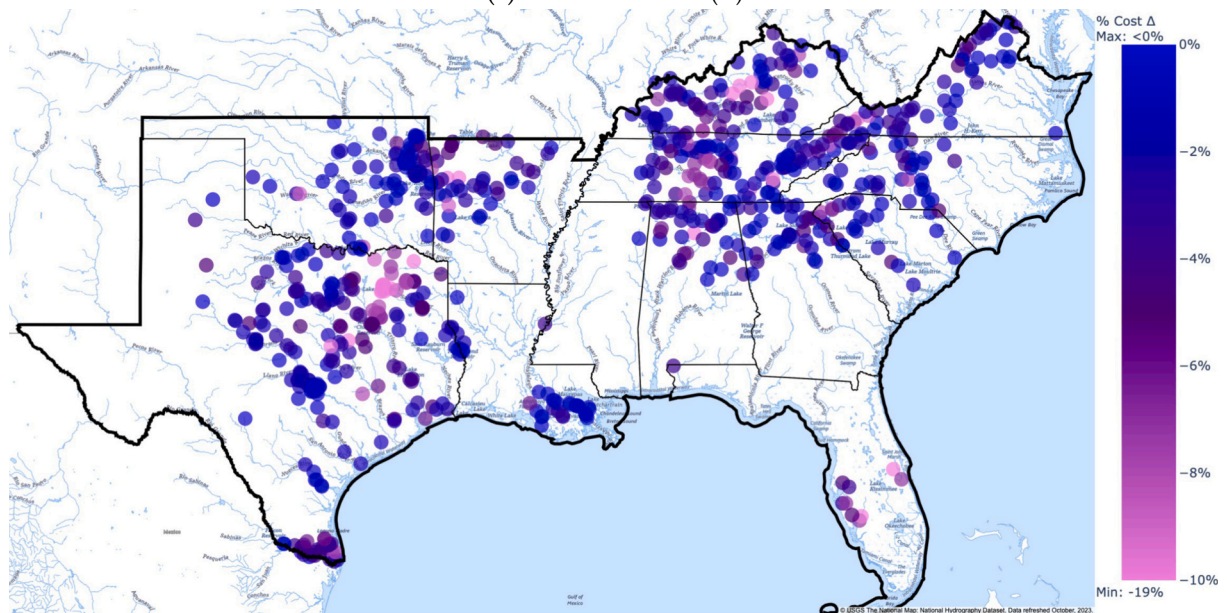


(b) Decrease in Costs (%)

Fig. 14. Map of facilities' projected cost changes (%) with change in total Phosphorus across the study region under the HadCEM2-ES climate scenario and Socioeconomic Pathway 3. Maximum percent change is 92 % and the minimum is -17 %.

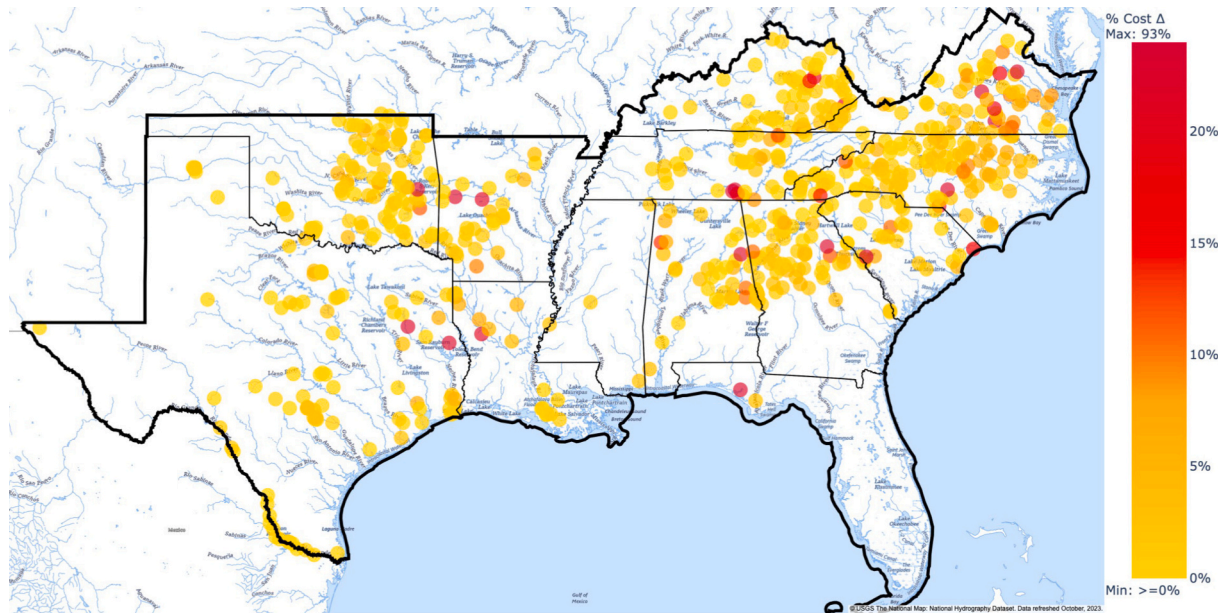


(a) Increase in Costs (%)

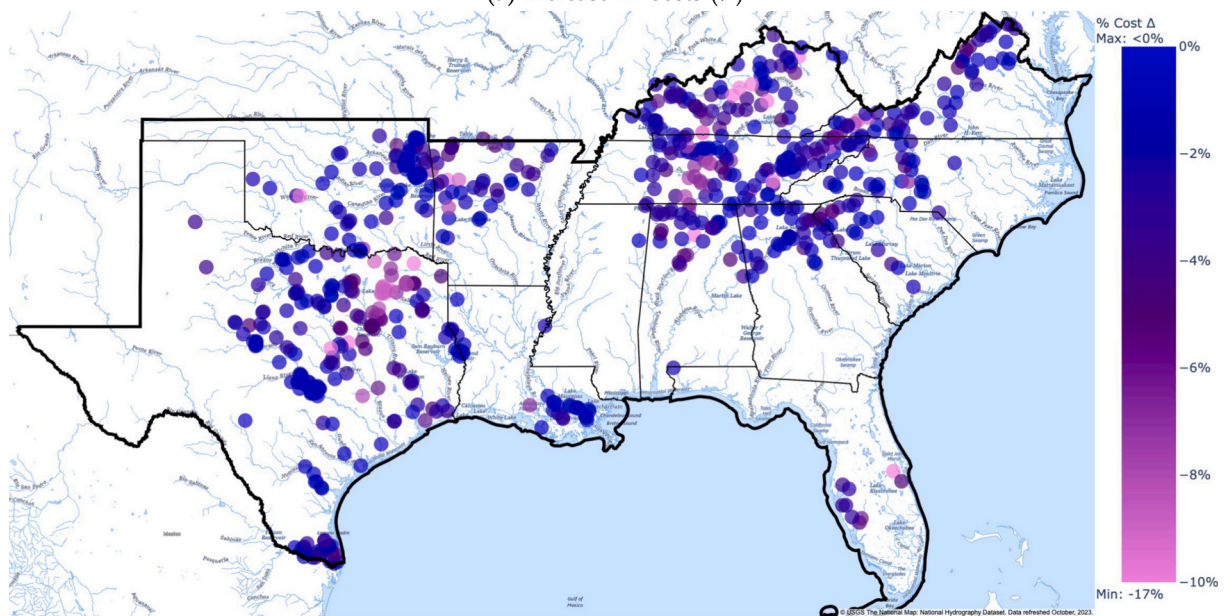


(b) Decrease in Costs (%)

Fig. 15. Map of facilities' projected cost changes (%) with change in total Phosphorus across the study region under the HadCEM2-ES climate scenario and Socioeconomic Pathway 5. Maximum percent change is 99 % and the minimum is −19 %.



(a) Increase in Costs (%)



(b) Decrease in Costs (%)

Fig. 16. Map of facilities' projected cost changes (%) with change in total Phosphorus across the study region under the MRI-CGCM3 climate scenario and Socioeconomic Pathway 3. Maximum percent change is 93 % and the minimum is -17 %.

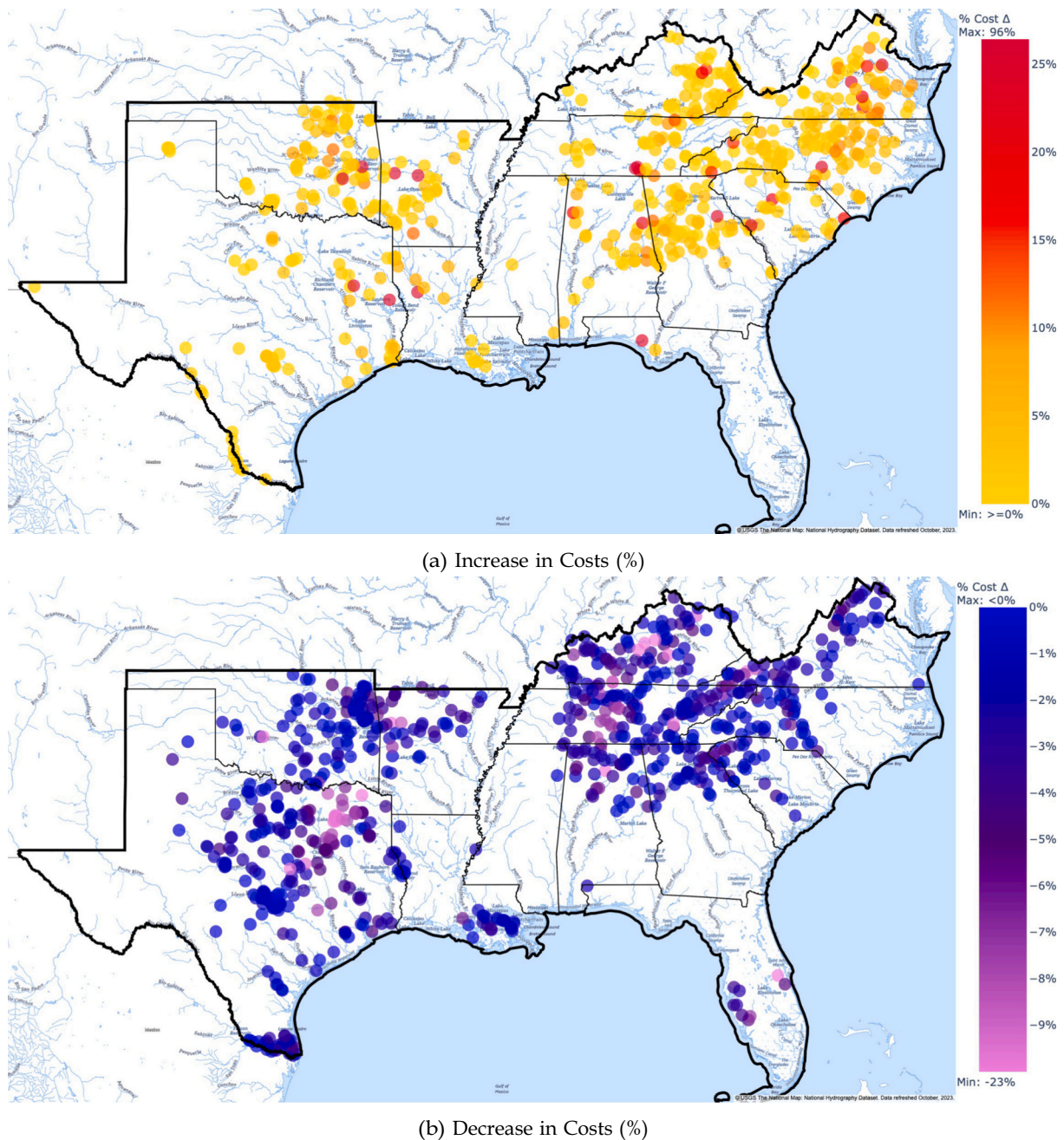


Fig. 17. Map of facilities' projected cost changes (%) with change in total Phosphorus across the study region under the MRI-CGCM3 climate scenario and Socioeconomic Pathway 5. Maximum percent change is 96 % and the minimum is -23 %.

A.11. Uncertainty analysis

The uncertainty analysis was conducted using models 3 and 4 (see Table 5). For each model we sampled 1000 times from the distributions defined by the parameters estimates and their standard errors. This results in 1000 models for nitrogen and another 1000 for phosphorus. Each of these models is then applied to the facility data and new estimates of baseline costs and projected scenario costs are developed. In this way each facility has 1000 predictions in the uncertainty dataset.

To better visualize the data, the facilities were binned into 8 groups based on their projected percent cost change for a given scenario. Those bins are [Min to -10 %), [-10 % to -5 %), [-5 % to 0 %), [0 % to 10 %), [10 % to 25 %), [25 % to 50 %), [50 % to 100 %), and [100 % to Max]. Here a square bracket represents inclusive and a curved parentheses represents non-inclusive. For example the second bin is defined as $\geq -10\%$ and $< -5\%$. The same bins were used across the different scenarios.

The boxplots were created using Matplotlib's boxplot function. The lower bar, therefore, represents the first quartile minus 1.5 times the interquartile range. The bottom of the box is then the first quartile value, the middle line the median, and the upper edge of the box the third quartile. The top bar is the third quartile plus 1.5 times the IQR. Outliers are omitted from the charts to improve readability. The rightmost, or 2, bins (bin 7 and/or 8) are separated out from the others to allow for a separate scaling on the y-axis as they tend to have the broadest uncertainty range.

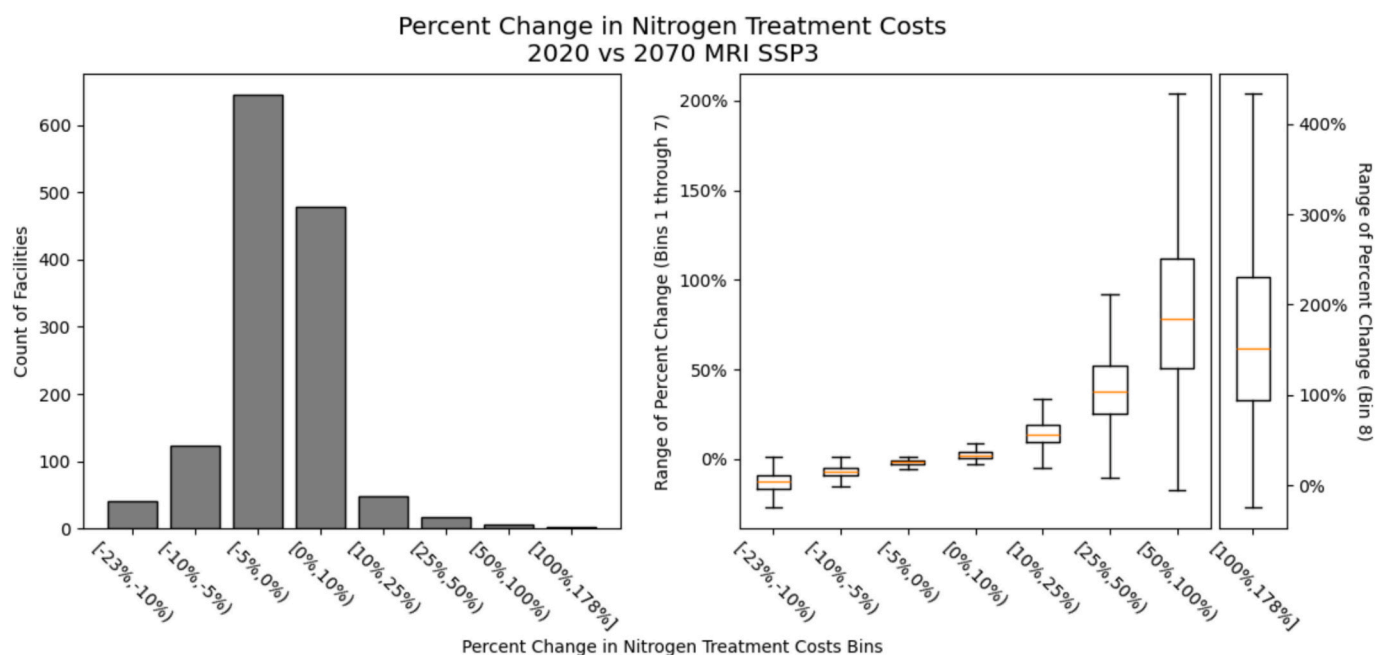


Fig. 18. Left: Distribution of facilities based on the predicted percent change in nitrogen costs under the MRI SSP 3 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

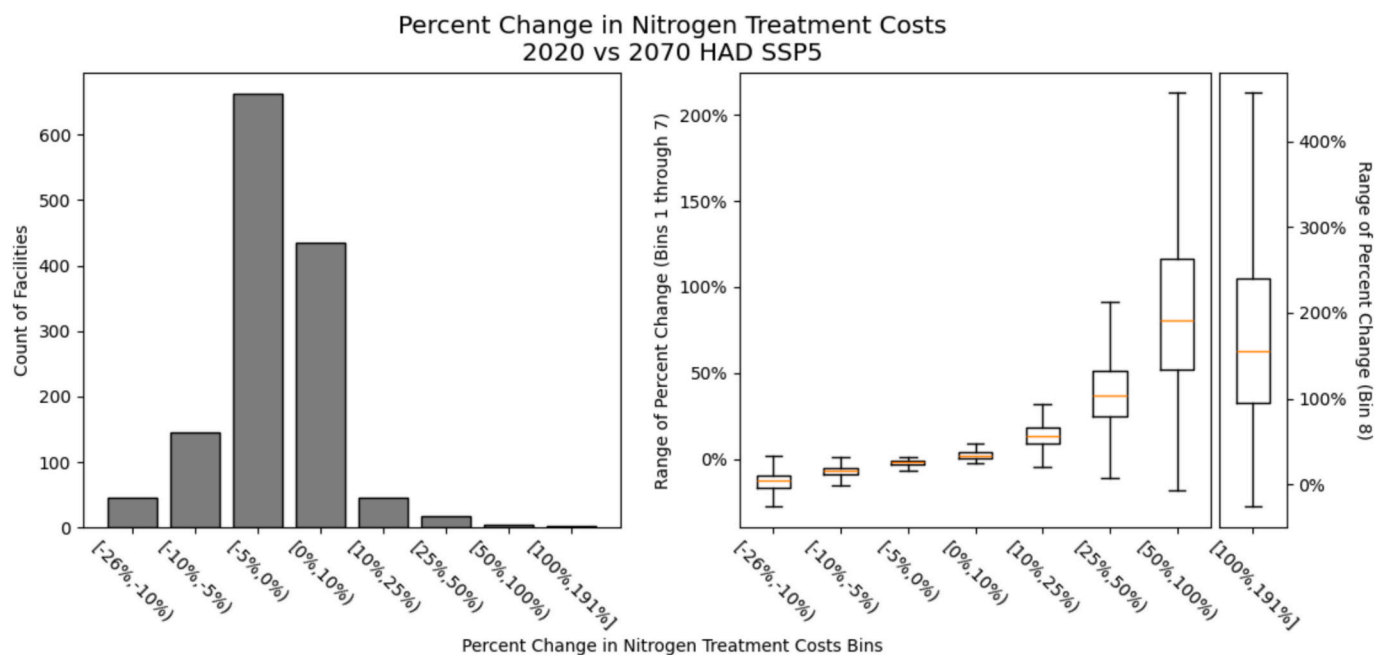


Fig. 19. Left: Distribution of facilities based on the predicted percent change in nitrogen costs under the HAD SSP 5 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

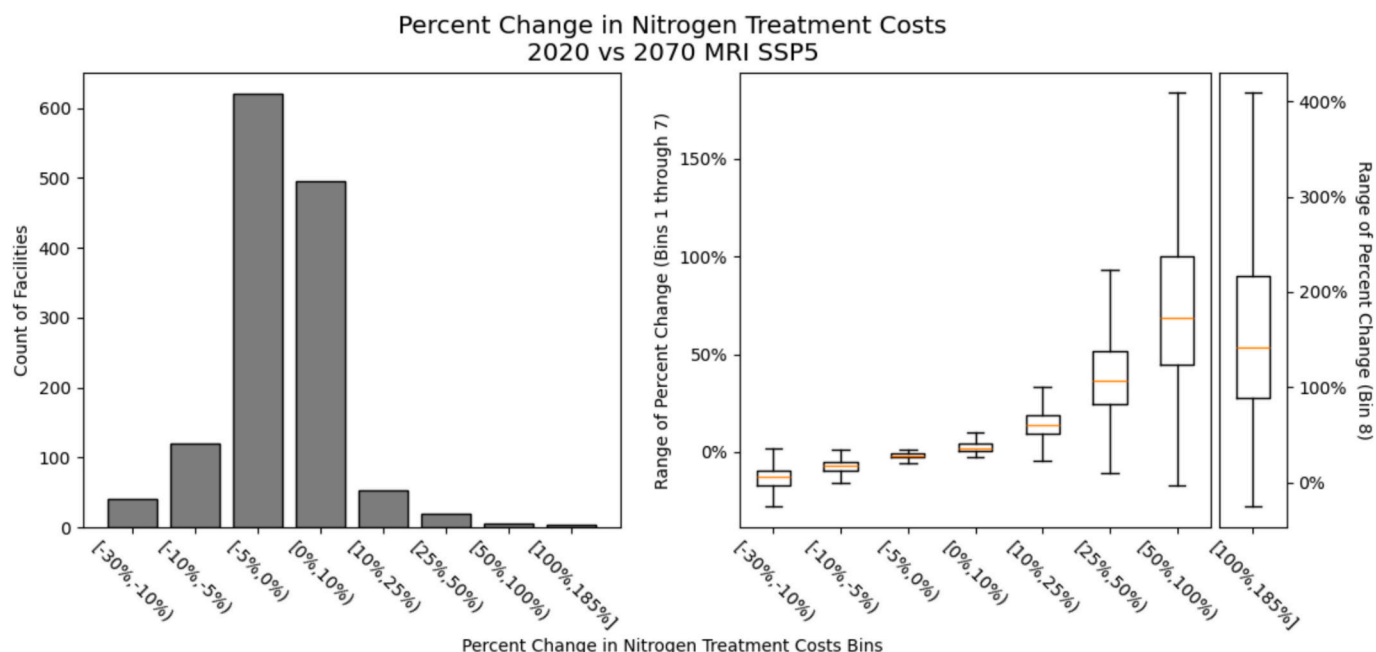


Fig. 20. Left: Distribution of facilities based on the predicted percent change in nitrogen costs under the MRI SSP 5 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

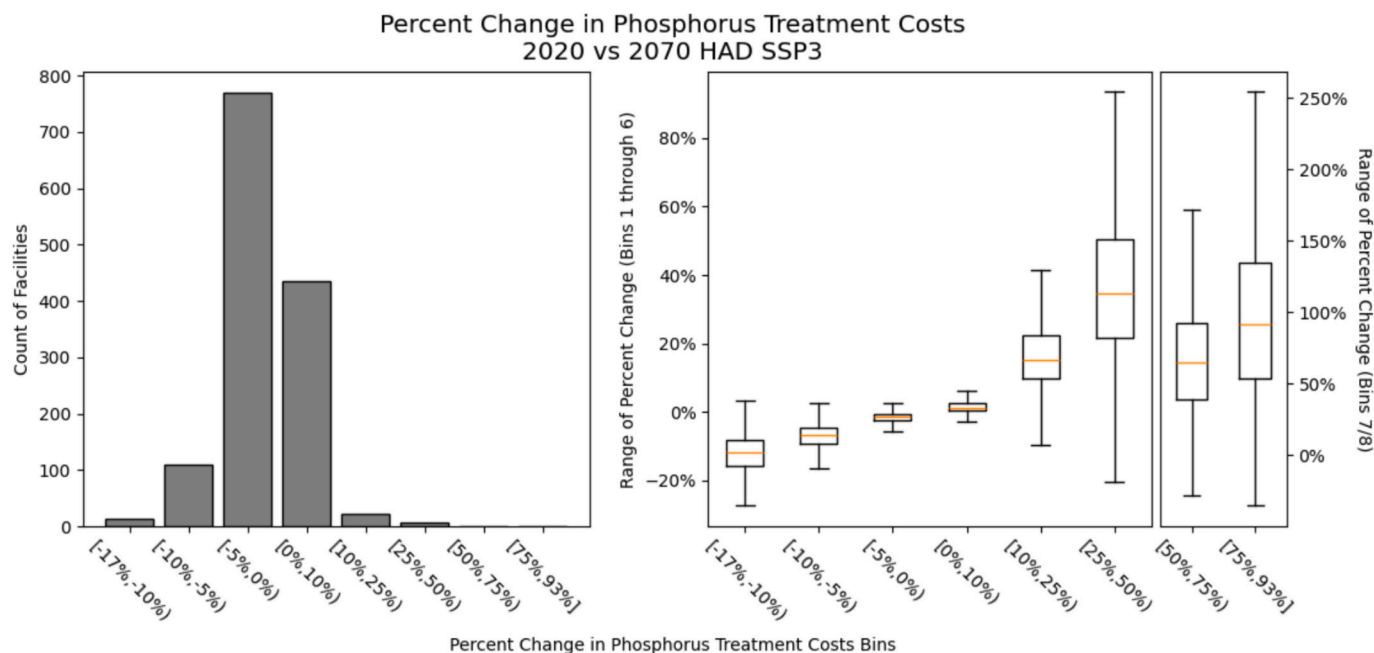


Fig. 21. Left: Distribution of facilities based on the predicted percent change in phosphorus costs under the HAD SSP 3 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

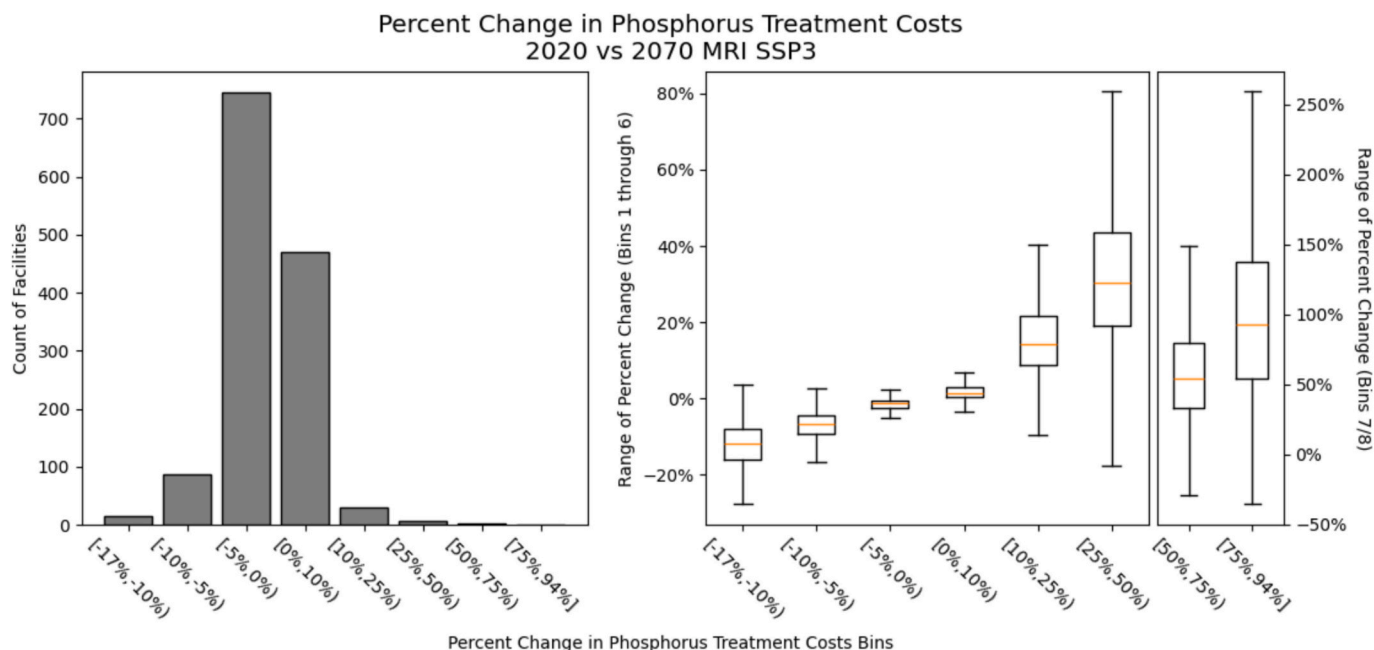


Fig. 22. Left: Distribution of facilities based on the predicted percent change in phosphorus costs under the MRI SSP 3 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

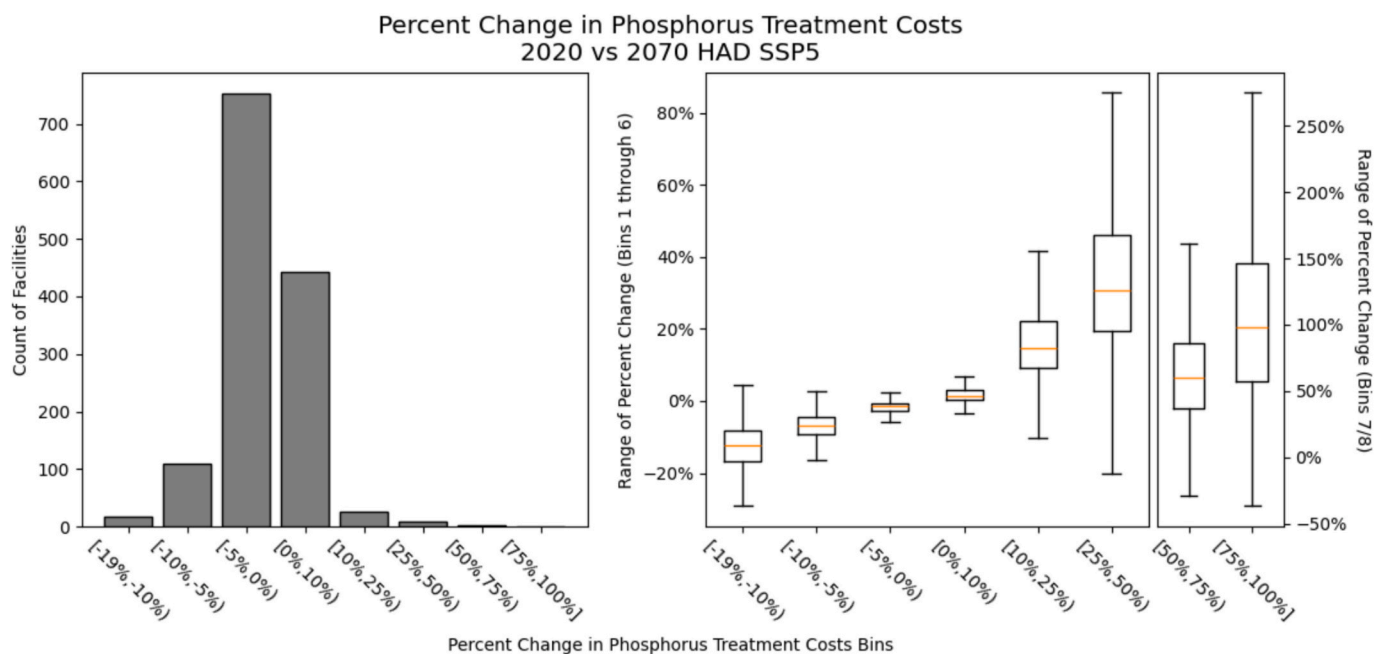


Fig. 23. Left: Distribution of facilities based on the predicted percent change in phosphorus costs under the HAD SSP 5 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

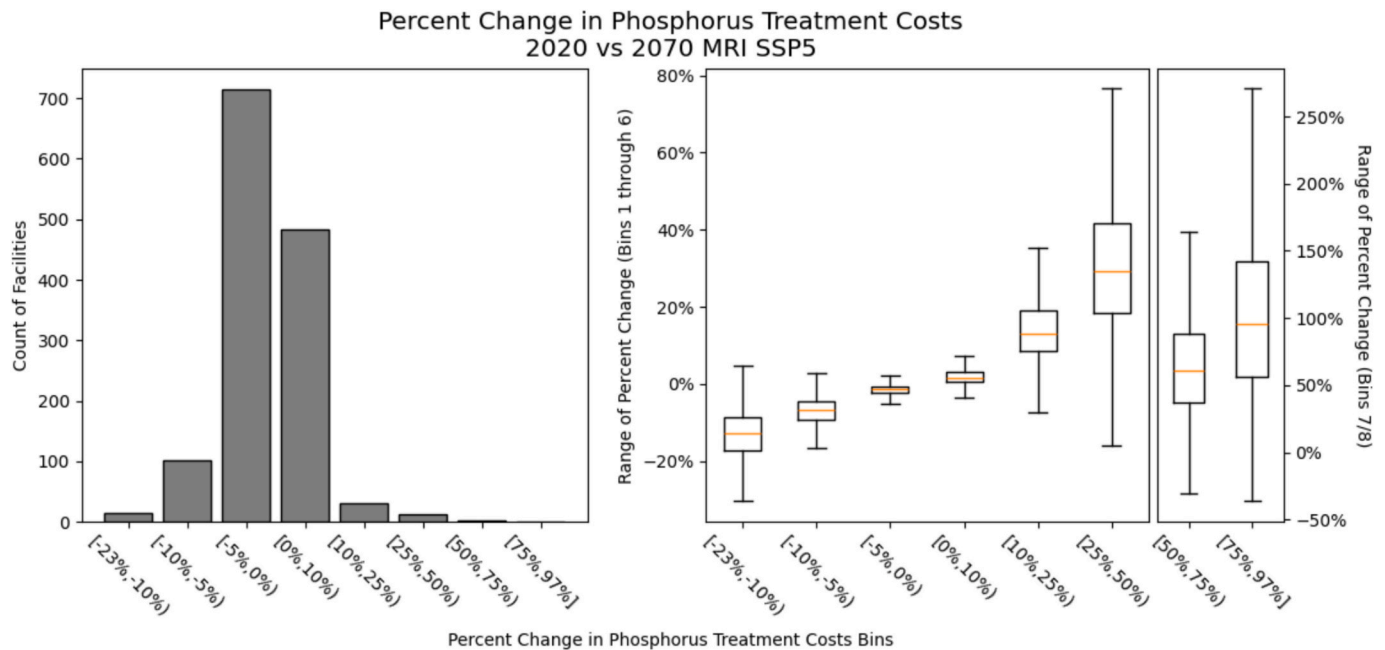


Fig. 24. Left: Distribution of facilities based on the predicted percent change in phosphorus costs under the MRI SSP 5 conditions. Right: Boxplots for each of the bins. Each facility is in this data 1000 times and belongs to a single bin for each of the scenarios.

Data availability

Data will be made available on request.

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