Valuation of Water Quality Change in Environment and Economy Context: Ecosystem Services and Biological Conditions across Gradients of Degradation and Local Economic Interest

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Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

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Abstract: This paper presents water quality valuation results based on a large-scale choice experiment in the Northeast U.S. The choice experiment is designed to determine the relative value of water quality investments and stream ecosystem restoration where residents may face explicit tradeoffs due to spatial complexity and social-economic heterogeneity. We collected choice experiment data using the Facebook advertising campaign that targets ordinary residents in the study areas. Results show that individuals value water quality and ecosystem service improvement differently across various levels of degradation. We also find that individuals hold different values in sites with different local economic contexts and ecosystem contexts, while there is no significance based on polluted economic activities. Our results have important policy implications by measuring the benefits and values of different attributes associated with water quality improvement.

Keywords: Non-Market Valuation, Choice Experiment, Stated Preference, Water Quality

JEL Codes: Q25, Q52, Q53, Q58

1. Introduction

Declining water quality has become a global issue during a period of climate change and population growth (Vörösmarty et al. 2000; Murdoch, Baron, and Miller 2000; Juma, Wang, and Li 2014). Agricultural intensification and economic development also impose additional pressure on the water resource (A. P. Smith, Western, and Hannah 2013; Juma, Wang, and Li 2014). The progress to accurately quantify water quality improvement benefits fall behind similar works on other environmental issues like air quality. Valuing water quality is considered challenging due to the heterogeneity in the degree of degradations in water bodies and the extent of spatial impact of water quality improvement approaches (Rode et al. 2010). Moreover, water resource is considered as a public good as well as a common pool resource (Savenije and van der Zaag 2002). The physical, political, and economic attributes associated with water resource (Rogers, Llamas, and Cortina 2005, Garrick et al. 2017) make it difficult to use a single metric to accommodate these different value dimensions (Espeland and Stevens 1998; Espeland 1998). Currently, policymakers lack the ability to decide whether a given investment in water quality returns a higher benefit than the investment cost compared with alternative choices, which complicates the decision-making process in the water quality restoration policies.

Existing water quality benefit estimates focus on an overall water quality improvement associated with a short-term surge. Few research has been conducted to assess the impacts of long-term marginal changes across gradients of degradation (Moore et al. 2018; Ji 2017; Van Houtven, Powers, and Pattanayak 2007; Viscusi, Huber, and Bell 2008). However, a discrete improvements of water quality in the relatively short term proposed by these studies are impractical for environmental regulation agencies such as EPA's benefit measurement. Environmental regulation agencies also have difficulty knowing whether an investment in the restoration of a severely degraded water body would return more or less benefit than a similar investment in a moderately degraded water body based on the existing studies (EPA 2015). Based on the diminishing marginal benefit principle, the first increments of water quality improvement (i.e., initial units of ecosystem restoration) return higher values (Arnold 2022), indicating that investment in severely degraded sites may be more cost effective. The change of ecosystems is discontinuous and could be irreversible after a specific polluted stage. Neglecting sudden, irreversible shifts to a higher degradation level may impose heavy costs to the society (Scheffer et al. 2001; Vandermeer and Yodzis 1999; Carpenter, Ludwig, and Brock 1999). For example, thresholds in ecosystem service production functions and resilience of water bodies experiencing regime shifts may necessitate largely, fixed investments before measurable improvements (Scheffer et al. 2001). Investments in moderately instead of severely degraded water bodies may return higher increments in ecosystem services related to water quality. This concern encourages us to consider heterogeneity in the status quo across different water bodies when measuring the value of a specific water quality change.

There is also limited guidance about how differences in spatial scales impact water quality benefits. The hydrology nature of water resources creates upstream-downstream interdependencies between users, leading to the so called "water asymmetry”. The downstream water users often depend on what upstream users do, whereas most of the time upstream users are not or little impacted by what downstream users do, at least within the water realm (van der Zaag 2007). As a result, actions that improve water quality upstream can affect the quality of downstream waters, thereby generating benefits far from the site of action. The water asymmetry phenomena require taking the individual users’ locations into account when valuing water quality improvement.

Moreover, most valuation studies conducted include a narrow range of water benefits by only capturing different segments or sources of overall benefits (V. K. Smith, Houtven, and Pattanayak 2002). One reason is the limitation of benefit measurements using current economic tools based on stated or revealed preferences. However, excluding certain benefits leads to an underestimation of total water quality benefits and complicates related water policies at the state or federal governments with an incomplete cost-benefit analysis. Many non-consumptive uses of freshwater are affected by water pollution, such as the endangerment of aquatic life and the alteration of ecosystems. An ideal water quality valuation framework should link measurable changes to the changes in individual values for non-human use value and ecosystem services (Keeler et al. 2012; EPA 2014; Van Houtven et al. 2014). Furthermore, the changes in non-consumptive value, such as ecological health, can result in obvious changes in water clarity, fish abundance, and algal blooms. These changes then affect ecosystem services like swimming and boating, as well as aesthetic factors like views and odors, and the safety of drinking water. Thus, the framework should also provide the potential explanations of the relative value of ecosystem service and non-consumptive improvement from the beneficiaries' perspective. Moreover, there may be publicly valued tradeoffs between water quality and other nature resources depending on the role of the water body in the local economy. For example, residents may be willing to sacrifice a certain degree of water quality in communities with employment depending on pollution-related industries. Thus, both ecological and economic characteristics at the study sites may be critical to water quality improvement valuation assessment.

To address existing research gaps and develop a generalized and transferable model that best fits statistical analyses of the relationship between water quality and values, we estimated the benefits of water quality changes in realistic scenarios where residents may face different tradeoffs accounting for spatial complexity and social-economic heterogeneity. In the paper, we define environmental and local-economy gradients by following the procedure proposed by Anderson (2008) to create representative indices based on a set of variables. This method provides a solid basis to aggregate multi-dimensional information into a single metric. We also constructed a stratified sampling strategy to select survey counties according to the environmental and local-economy gradients at a county level.

Our model also constructs a water quality framework that links measurable changes to the changes in individual values for ecosystem services and non-human use values (Davies and Jackson 2006; Mitchell and Carson 1986). Existing literature proposes several methods to convey information regarding water quality and relevant natural processes to the public, among which the most widely used is the water quality ladder (Mitchell and Carson 1986; Desvousges, Smith, and Fisher 1987; Kataria et al. 2012). The water quality ladder is based on an ecosystem service for water bodies, from the non-useable, to suitable for boating, fishing, and then swimming (Van Houtven, Powers, and Pattanayak 2007). A standardized water quality ladder score enables us to compare benefit estimates across study sites, serving as the primary foundation for placing specific sites on a biophysical gradient. In addition, EPA has developed the Biological Condition Gradient (BCG) as a common assessment tool independent of individual physical, chemical, or biological assessments of water bodies, focusing on the non-use value (Davies and Jackson 2006). The BCG can be divided into four general categories applicable to our study, with “none or few”, “some”, “many” and “most or all” species in the water bodies. While the BCG provides a framework to define non-use values of water bodies, it is also related to designated uses. By coupling the ecosystem service and BCG scores, we establish a clear target in the site sampling procedure that accommodates both the use and non-use values.

The purpose of this study is to provide a set of transferable estimates, preference models, and guidelines for application. We set three specific objectives for our analysis: 1) Measure the relative value or benefits of water quality investments and stream ecosystem restoration in sites that are heavily degraded versus sites that are only moderately degraded and have the potential to produce a substantial set of ecosystem services. 2) Measure how the value or benefits of water quality and ecosystem restoration is affected by the location of the water streams (in the county, upstream, downstream, or disconnected). 3) Measure how the value or benefits of water quality and ecosystem restoration is affected by the local economic and ecosystem context; and the context of where the streams are relative to current and past economic activities, especially jobs in pollution-intensive industries versus other employment.

The remainder of the paper is organized as follows. Section 2 outlines the experimental design, survey development and implementation. Section 3 describes the conceptual model for analyzing discrete choices, drawing from random utility models. Section 4 presents the preliminary results of hypothesis testing and Section 5 concludes and discusses the implications of the results.

2. Experimental Design

2.1. Study Location

Our surveys were created to provide a representative valuation in the northeastern U.S. communities. The study region includes 11 states (MD, NJ, DE, PA, NY, CT, RI, MA, VT, NH, and ME). We developed three indices - Socio-Economic, Ecological Integrity, and Pollution Economy - to capture the environmental and economic situation for each county. Based on which we assigned all selected 215 counties to five different clusters. In the sample frame, we eliminated island counties, counties with a population density of more than 2,500 persons per square mile, and counties with fewer than 7,000 households in the Northeast States. Then, we chose 20 counties for our survey instrument by randomly selecting 4 counties from each cluster.

The three indices were created using the technique Anderson (2008) proposed, which was based on the weighted mean of many standardized variables. The weights (w_k) of each variable were determined in order to maximize the quantity of information captured. The specific steps are as follows: 1) We switched the signs of all k variables (y_k) included in creating the indices wherever necessary to guarantee that the positive direction always denotes a better or worse result. 2) We then created standardized variables $(\tilde{y}_k)$ by demeaning y_k and then dividing by the standard deviation σ_k^y. 3) We obtained the covariance matrix $\hat{\Sigma}$ using the following formula

$$\hat{\boldsymbol{\Sigma}}_{\boldsymbol{mn}} = \sum_{i=1}^{N_{mn}} \frac{y_{im} - \bar{y}_m}{\sigma_m^y} * \frac{y_{in} - \bar{y}_n}{\sigma_n^y} = \sum_{i=1}^{N_{mn}} \tilde{y}_{im} * \tilde{y}_{in} (1)$$

where N_{mn} is the total number of counties involved in the study, and m and n are all possible combinations of the two variables selected from the k variables. 4) We inverted the covariance matrix and define the weight w_k for each variable k by summing the entries in each row of the inverted covariance matrix following

$$\hat{\Sigma}^{-1} = \begin{bmatrix} c_{11} & \cdots & c_{1K} \\ \vdots & \ddots & \vdots \\ c_{K1} & \cdots & c_{KK} \end{bmatrix}$$

$$w_k = \sum_{l=1}^{K} c_{kl}. \qquad (2)$$

5) We created a new variable called $\hat{y}_i$, which was the weighted average of $\tilde{y}_{ik}$ for county i.

$$\hat{y}_i = \left(\sum_{k \in K} w_k\right)^{-1} \sum_{k \in K_i} w_k * \frac{y_{ik} - \bar{y}_k}{\sigma_k^y}. \quad (3)$$

After understanding how to generate three indices, the related variables are then introduced. The Socio-Economic index was developed using data from the recent American Community Survey (ACS) conducted by the U.S. Census Bureau, including median household income, per capita personal income, median home value, median rent, population density, average employment rate, percentage of adults with college degrees, and percentage of people of all ages not living in poverty.

For the Pollution Economy index, we first used the Anderson (2008) method to construct an aggregate pollution intensity variable by combining three standardized pollution variables generated from various pollution data sources, including the Toxics Release Inventory (TRI), the National Pollutant Discharge Elimination System (NPDES), and the Resource Conservation and Recovery Act (RCRA). Then, we calculated an industry-related pollution economic score using

$$\mathrm{PollutionEconomy}_{\mathrm{c}}^{\mathrm{industry}} = \sum_{i=1}^{I} PollutionIntensity_i * \left(\frac{Employment_{ic}}{Population_c}\right). \quad (4)$$

Similarly, we calculated an agriculture-related pollution economy score for each county using

$$\mathrm{PollutionEconomy}_{\mathrm{c}}^{\mathrm{farm}} = \frac{Total\ Nutrients_c - \min\{Total\ Nutrients\}}{max\{Total\ Nutrients\} - \min\{Total\ Nutrients\}} * \left(\frac{Farm\ Employment_c}{Population_c}\right). \ (5)$$

By combining $\mathrm{PollutionEconomy}_{\mathrm{c}}^{\mathrm{industry}}$ and $\mathrm{PollutionEconomy}_{\mathrm{c}}^{\mathrm{farm}}$, and weighting the proportion of non-farm and farm employment in each county, we finally established an overall pollution economy index using

$$PollutionEconomy_c^{combined} = \frac{Non\!-\!farm\ Employment_c}{Total\ Employment_c} * PollutionEconomy_c^{ind}$$

$$+ \quad \frac{Farm\ Employment_c}{Total\ Employment_c} * PollutionEconomy_c^{farm}. \quad (6)$$

The Ecological Integrity Index for the Northeast region used in this paper was created by McGarigal et al. (2018). The index of ecological integrity (IEI) measures the degree to which an ecosystem is relative intact (i.e., not adversely altered or disturbed by humans) and resilient to environmental change (i.e., capacity to recover from or adapt to changing environmental conditions driven by human land use and climate change). The IEI is a composite index created from up to 20 different landscape metrics, each of which measures a different component of intactness (e.g., road traffic intensity, percent impervious) and/or resiliency (e.g., ecological similarity, connectedness) and applied to each 30 m cell (see more details in McGarigal et al. (2018), Table 2). Ecological Integrity Index at the county level is obtained by taking a simple average of the index values of all 30m cells that fall within a county.

Then we cluster the sample counties based on the three indices. To determine the optimal number of clusters, we used three methods including the elbow, silhouette, and gap statistics. The elbow method is to define clusters such that the total intra-cluster variation (known as total within-cluster variation or total within-cluster sum of square) is minimized. The average silhouette approach measures the quality of a clustering by determining how well each object lies within its cluster. A high average silhouette width indicates good clustering. The gap statistic compares the total intra-cluster variation for different values of cluster *k* with their expected values under the null reference distribution of the data. To minimize the within-cluster sum of square, maximum average silhouette width, and maximize the gap statistic, our results suggest 5 clusters perform well on all the three measures. For each of the 5 clusters, we randomly picked 4 counties within each cluster (Figure 1).

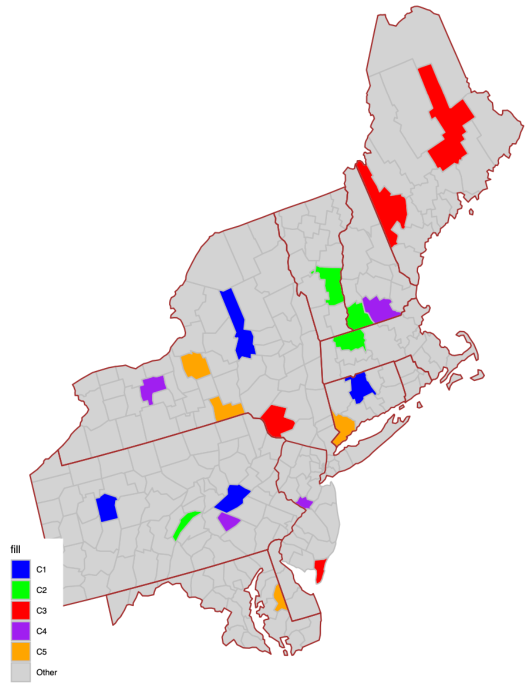

Figure 1. Sample Counties.

2.2. Survey Design, Development, and Implementation

We conducted a number of in-depth interviews with water quality experts and several focus groups across the Northeast US to develop the choice survey. By using the focus group, survey materials were created, improved, and pre-tested for the comprehensiveness of management choices, clarity, and consistency of communication between survey participants and researchers (Johnston et al. 1995). The focus groups took place in the following locations: Syracuse, NY; East Greenbush, NY; Holyoke, MA; Bethlehem, PA; and Laureldale, PA. The discussions led us to use separate bar graphs to represent the levels (number of river miles) in each water quality category and describe alternative programs presented in choice questions. Based on the feedback from focus groups and interviews, we determined six attributes and corresponding levels concerning biological conditions linked to ecosystem service as well as locations. Table 1 lists the final set of attributes and corresponding levels. The attribute levels we chose allow us to assess the degree of water quality and tradeoffs that are important to the general population. Our choice experiment design also allowed us to measure willingness to pay (WTP) for a wide range of the water quality scale rather than only a small or moderate shift in the mean value of water quality improvement, as was the case in previous research.

Table 1. Attributes and attribute levels.

Attribute	Attribute levels
Human Use Score (X^h)	Swimmable; Fishable; Boatable; Unusable
A Breakdown of how river miles may change for Human Use ($X^{\Delta h}$)	Number of miles that change from: Unusable to Boatable; Unusable to Fishable; Boatable to Fishable; Boatable to Swimmable; Fishable to Swimmable
Ecological Integrity Index Score (X^e)	"Most or all" species; "Many" species; "Some" species; "None or few" species
A Breakdown of how river miles may change for the Ecological Integrity Index ($X^{\Delta e}$)	Number of miles that change from: "None or few" to "Some"; "None or few" to "Many"; "Some" to "Many"; "Some" to "Most or all"; "Many" to "Most or all"
Location (S^{loca})	In your county; Receive water from your county (Only for Version 1); Send water to your county (Only for Version 1); Disconnected ((Only for Version 1)
Cost/year for 10 years ($Cost$)	$0 $40 $60 $100 $250 $300 $500

By maximizing the statistical efficiency, we created a minimal set of choice questions based on the collection of attributes using Ngene Software. In addition, we designed two versions of the choice question to distinguish the impact of a real and hypothetical water quality baseline in respondents' valuations in water quality improvement. Specifically, in the first version, one current water quality status information was presented in the survey as the baseline scenario, and two alternatives for improving the water quality were offered (Appendix A). This version made it possible to measure respondent's willingness to pay for enhancing water quality. The second version included two hypothetical baseline scenario and one result for improved water quality (Appendix B). This version made it possible to measure respondent's willingness to accept compensation for staying the status quo. For each version, we generated 9 sets of plans to enhance water quality. Each participant was directed to complete one randomly selected set from version 1, consisting of four choice questions, and one randomly selected set from version 2, consisting of three choice questions. Respondents needed to select one option among two alternative choices associated with different water quality improvement plan and one choice for the "No action" choice, i.e., the status quo alternative. It was made clear to respondents whether the baseline is real. It is worth emphasizing that our main focus in the primary context was on utilizing version 1 for analysis and capturing respondents' willingness to pay (WTP) for water quality improvement. The analysis of version 2, on the other hand, was employed as a supplementary approach in our study. Moreover, we gathered the respondents' subjective perceptions of water pollution, environmental attitude, and household basic information.

Survey respondents were recruited through extensive advertising campaigns on Facebook in 2021. We carried out five separate campaigns, each corresponding to one of the five clusters representing the counties within our study area. The reason for conducting separate campaigns in different clusters was to ensure targeted recruitment of respondents, allowing for a balanced sample by including counties with low population density. This was necessary because Facebook's advertising algorithms tend to prioritize high-density counties while excluding those with lower population density. Table 2 provides information on the number of surveys completed in each county, totaling 3176 completed surveys. The frequency column indicates the number of completed surveys, while the percentage columns depict the proportion of completed surveys within each county relative to the entire sample. In addition, Table 2 provides the population data for each county in 2021.

Table 2. Observations by county.

Cluster	County	Frequency	Percentage	Population (2021)	Rural-Urban Continuum Code 2013
1	Jefferson, PA	93	3%	44,114	7
	Hartford, CT	286	9%	896,854	1
	Herkimer, NY	118	4%	59,937	2
	Schuylkill, PA	200	6%	143,264	4
2	Juniata, PA	102	3%	23,297	6
	Windsor, VT	106	3%	58,196	7
	Cheshire, NH	174	5%	77,329	4
	Franklin, MA	158	5%	71,015	4
3	Oxford, ME	198	6%	58,629	6
	Penobscot, ME	297	9%	152,765	3
	Sullivan, NY	55	2%	79,806	4
	Cape May, NJ	97	3%	95,661	3
4	Hillsborough, NH	180	6%	424,079	2
	Lebanon, PA	116	4%	143,493	3
	Ontario, NY	102	3%	112,508	1
	Mercer, NJ	157	5%	385,898	2
5	Broome, NY	104	3%	197,240	2
	Caroline, MD	133	4%	33,386	6
	Fairfield, CT	291	9%	959,768	2
	Onondaga, NY	209	7%	473,236	2
Total Observation				3,176	

2.3. Basic Summary Statistics

Table 3 presents the summary statistics of the participants included in the analysis, encompassing their environmental attitudes, pollution perception, and socio-demographic characteristics. Additionally, the table also provides the standard social economic, ecological integrity, and pollution economy index at an individual’s that were generated in Section 2.1.

Regarding the socio-demographic characteristics of the individuals, we primarily considered age, gender, race, income, and education levels. The median age of the survey participants was found to be 38. In terms of gender distribution, slightly over half of the sample (55%) comprised females, which is higher than the overall equivalent gender ratio in the U.S. Additionally, our sample exhibited a relatively lower representation of minority groups (less than 10%) compared to the data from the American Community Survey (ACS). Around 37% of the survey participants in our study possessed a bachelor's degree or higher, which aligns with the percentage of individuals in the United States who held such degrees in 2021. However, concerning income distribution, approximately 92% of the survey participants reported an annual income below $100,000, while around 7% reported an income exceeding $100,000 per year. Additionally, approximately 1% of the participants did not disclose their income. In contrast, in 2021, about 64% of the general population had an income below $100,000, whereas approximately 36% had an income exceeding $100,000 per year.

Table 3. Socio-demographic characteristics and environmental attitudes.

Continuous variables		Mean	SD	N
Pro-Tax Policy		0.0005	1.0180	3,176
No-Government Trust		0.0061	1.1371	3,176
Pro-Water Conservation		-0.0067	1.2497	3,176
Perception of water pollution		-0.0028	1.1966	3,176
Perception of household contribution in adding pollutants to water (0~100)		27.2415	13.9222	3,176
Standard Socio-economic Index		0.0116	0.7969	3,176
Standard Aquatic Integrity Index		0.0142	1.1019	3,176
Standard Pollution Economy Index		0.2056	0.9050	3,176
Categorical variables		**Frequency**	**Percentage**	**N**
Age				3,176
	<=18	151	4.75	
	(18,30]	762	23.99	
	(30,45]	1,294	40.74	
	(45,60]	609	19.18	
	(60,75]	330	10.39	
	>75	30	0.94	
Gender				3,176
	Female	1,736	54.66	
	Male	1,440	45.34	
Race				3,176
	White	2,901	91.34	
	Black or African American	142	4.47	
	Hispanic	100	3.15	
	Asian	16	0.5	
	Other	17	0.54	
Income				3,176
	Prefer not to say	37	1.16	
	Under $25,000	19	0.6	
	$25,000-$49,000	270	8.5	
	$50,000-$74,999	1,647	51.86	
	$75,000-$99,999	979	30.82	
	$100,000-$149,000	167	5.26	
	$150,000-$199,999	47	1.48	
	$200,000 or more	10	0.31	
High Education				3,176
	Bachelor's Degree or Higher	1,179	37.12	
	Lower than Bachelor	1,997	62.88	

Factor analysis (Kaiser 1958; Harman and Harman 1976; Tarlov et al. 1989) was utilized to construct the Pro-Tax Policy, No-Government Trust, Pro-Water Conservation, and Perception of water pollution variables. Table 4 displays the results of the factor analysis investigating environmental attitudes. Participants in the survey rated nine attitude statements on a seven-point Likert scale, ranging from "Strongly agree" to "Strongly disagree". Using the "pca" statistical package in Stata, we derived three continuous-valued factors from these ratings. The rotated factor loadings in Table 4 for each statement represent the corresponding principal components of the three continuous-valued factors (Milan and Whittaker 1995). The highest-ranking factor, suggesting an attitude favoring water conservation, has been labeled as "Pro-Water Conservation". The second ranked factor indicates participants' trust in government and is therefore labeled as "No-Government Trust". Similarly, the third ranked factor demonstrates a favorable attitude toward tax policy for enhancing water quality and is labeled as "Pro-Tax Policy".

Table 4. Rotated factor loadings on Likert-scale attitudinal statements about water conservation.

Statements [a]	Factor 1	Factor 2	Factor 3
	Pro-Water Conservation	No-Government Trust	Pro-Tax Policy
I think my state would adopt a taxing approach similar to Missouri	0.0308	-0.2418	**0.7301**
Governments should use existing revenue to pay for conservation	0.2804	0.2100	**0.5450**
I am against more government spending	-0.2224	**0.5313**	0.0520
I do not trust the government to make proper use of tax money	0.1433	**0.5717**	0.1243
I think conservation is important	**0.4821**	0.0194	0.0534
Polluting entities should pay for conservation	**0.4413**	0.1291	-0.0119
Only those who use the water bodies regularly should pay for their conservation	-0.3268	**0.4790**	-0.0123
I am willing to help communities upstream do more to protect water quality in rivers and streams	**0.3619**	0.2046	-0.1436
Since food, waste, and activities of my household can contribute to pollution, I am willing to pay some of the costs of water quality improvement directly	**0.4308**	0.0022	-0.3579

[a] Survey participants rated each statement using a seven-point Likert-scale varying from Strongly Agree (1) to Strongly Disagree (7). Numbers in bold represent varimax rotated highest factor loading (normalized to mean 0 and SD 1) for a given statement indicating agreement for positive coefficient and vice versa. Total variation explained by the three factors is 43.24 %.

We employed the same methodology to determine participants' perceptions of water pollution. This involved using four statements to assess their ratings of water impairment caused by trash, chemical pollutants, biologically based pollutants, and nutrients. Additionally, we inquired about participants' perception of their household contribution to water pollution, on a scale ranging from 0 to 100, by asking: "How significant is the relative contribution of you and your household, through products you purchase and consume and through your daily activities, in adding pollutants to water?" To ensure accuracy, we provided instructions regarding the sources of water pollutants. The average score obtained in this study, as indicated in Table 3, is approximately 27, suggesting a relatively low perception among participants regarding their contribution to water pollution.

3. Model Specification and Hypothesizes

3.1. Random Utility Model (RUM) Framework for Discrete Choice Experiments

We model respondent's preferences for water quality investments and stream ecosystem restoration alternatives within discrete choice experiments based on the random utility model (RUM), which has been widely used in the stated preference studies (e.g., McFadden 1974; Hanemann 1984; Mitchell and Carson 1986; Opaluch et al. 1993; Adamowicz et al. 1998). The RUM assumes that respondents evaluate the attributes of a set of alternatives and choose the alternative with the highest utility. In our water quality application, respondents are asked to choose among two alternative options, labeled as "A" and "B", or to retain the status quo ("No action").

In a random utility model, a representative indirect utility function is assumed to include an observable, deterministic part (or V_{ij} for an household i from alternative j) as well as an unobservable component (e_{ij}). The error term (e_{ij}) is assumed to be independently and identically distributed (iid) according to Gumbel distribution. The p_{ij} represents the probability that individual i selects an alternative j in the choice set C given by a conditional logit model specification:

$$\Pr(j) = \prod p_{ij} = \frac{\exp\,(V_{ij})}{\sum_{j'} \exp\,(V_{ij'})} \quad (7)$$

where j' is an index of summation across all available options in C. The deterministic part V_{ij} is a function of a vector of perceived attributes (X_{ij}) within the jth alternative for individual i. Moreover, the value of water quality improvement and ecosystem restoration can be influenced by various factors including the local economic context, ecosystem/degradation context, socio-demographic characteristics, and environmental attitude and perception. In addition, the local economic context, ecosystem/degradation context, as well as socio-demographic characteristics and environmental attitude can influence the value of water quality improvement. As a result, the indirect utility function V_{ijm} is assumed to have a linearly additive form, as is described in equation (8). In this equation, S_i represents a vector of an individual or county-specific characteristics for individual i, η_i represents the site-specific fixed effects to account for all time-invariant site-specific attributes, and SQ_j denotes the alternative specific constant (ASC) taking the value of 1 for the "No Action" and a value of 0 for alternative options (A or B).

$$V_{ij} = \sum_{h=1}^{K} \beta_h X_{ihj} + SQ_j(\alpha + \sum_{k=1}^{K} \alpha_k S_{ik} + \eta_i). \quad (8)$$

3.2. Empirical Model Specification

We assume the conditional indirect utility is a linear function of current water quality attributes and the water quality changes. In Eq. (9), we specify a full model and then we test the different parameter restrictions of interest against the full specification to derive a representative utility function. Specifically, we have

$$V_{ij} = (\sum_{h=1}^{H} \beta_h^H X_{ihj}^h + \sum_{e=1}^{E} \beta_e^E X_{iej}^e + \sum_{\Delta h=1}^{\Delta H} \beta_{\Delta h}^{\Delta H} X_{i\Delta hj}^{\Delta h} + \sum_{\Delta e=1}^{\Delta E} \beta_{\Delta e}^{\Delta E} X_{i\Delta ej}^{\Delta e} + \beta_c Cost_{ij}) + SQ_j(\alpha$$

$$+ \sum_{k=1}^{K^{loca}} a_k^{loca} S_{ik}^{loca} + \sum_{n=1}^{N^{demo}} \sum_{k=1}^{K^{demo}} a_{nk}^{demo} S_{ink}^{demo} + \sum_{k=1}^{K^{att}} a_k^{att} S_{ik}^{att} + \sum_{k=1}^{K^{per}} a_k^{per} S_{ik}^{per}$$

$$+ a^{SE} S_i^{SE} + a^{EI} S_i^{EI} + a^{PE} S_i^{PE} + \eta_i \ ) \quad (9)$$

where X_{ihj}^h represents the number of miles associated with human use score h for individual *i* for option *j*. Similarly, X_{iej}^e represents the number of miles associated with ecological integrity score e for individual *i* for option *j*. $X_{i\Delta hj}^{\Delta h}$ represents the number of miles when the human use score experiences an improvement of Δh for individual *i* for option *j*. Likewise, $X_{i\Delta ej}^{\Delta e}$ represents the number of miles when the ecological integrity score experiences an improvement of Δe for individual *i* for option *j*. The cost of each year to the household of individual I for option *j* is given by $Cost_{ij}$. Additionally, S_{ik}^{loca} represents the location attribute *k* associated with individual *i*. S_{ilk}^{demo} represent the level of demographic variable k for individual *i,* including age, gender, race, household income, and individual i's level of education. S_{ik}^{att} represents the environmental attitude variable k for individual *i.*[1] S_{ik}^{per} represents the subjective perception variable k for individual *i.*[2] $S_i^{SE}, S_i^{EI}, and\ S_i^{PE}$ represents the social economic index, ecological integrity, and

[1] We used Principal Components Analysis (PCA) to generate three continuous factor scores representing different aspects of environmental attitude.
[2] We also used PCA to generate one factor scores representing the subjective perception of water pollution.

pollution economy index at the individual i's site, respectively. And η_i captures the site-specific fixed effects, incorporating all site-specific attributes that remain constant over time.

$$V_{ij} = (\sum_{h=1}^{H} \beta_h^H X_{ihj}^h + \sum_{e=1}^{E} \beta_e^E X_{iej}^e + \sum_{\Delta h=1}^{\Delta H} \beta_{\Delta h}^{\Delta H} X_{i\Delta hj}^{\Delta h} + \sum_{\Delta h=1}^{\Delta H} \beta_{\text{Inte}\Delta h}^{\Delta H} X_{i\Delta hj}^{\Delta h} \times H_{current}$$

$$+ \sum_{\Delta e=1}^{\Delta E} \beta_{\Delta e}^{\Delta E} X_{i\Delta ej}^{\Delta e} + \sum_{\Delta e=1}^{\Delta E} \beta_{\text{Inte}\Delta e}^{\Delta E} X_{i\Delta ej}^{\Delta e} \times E_{current} + \beta_c Cost_{ij}) + SQ_j(\alpha$$

$$+ \sum_{k=1}^{K^{loca}} a_k^{loca} S_{ik}^{loca} + \sum_{l=1}^{L^{demo}} \sum_{k=1}^{K^{demo}} a_{lk}^{demo} S_{ilk}^{demo} + \sum_{k=1}^{K^{att}} a_k^{att} S_{ik}^{att} + \sum_{k=1}^{K^{per}} a_k^{per} S_{ik}^{per}$$

$$+ a^{SE} S_i^{SE} + a^{EI} S_i^{EI} + a^{PE} S_i^{PE} + \eta_i) \quad (10)$$

To explore whether respondents assign consistent values to water quality improvements across different current levels, we introduced interaction terms involving the utility parameters $X_{i\Delta hj}^{\Delta h}, X_{i\Delta ej}^{\Delta e}$ with the current status of water quality level and human use level, as depicted in Equation (10). In this equation, $H_{current}$ represents the current human use level, and $E_{current}$ represents the current ecological integrity level. We considered two different measures for the current variables of human use and ecological integrity levels: (1) the average score and (2) the rank classification, including high, middle, and low levels of current water quality.

To estimate the potential impact of the real or hypothetical water quality baseline scenario presented in the choice questions on the perceived value of water quality and ecosystem service improvement, we also introduced interaction terms involving the utility parameters $X_{i\Delta hj}^{\Delta h}, X_{i\Delta ej}^{\Delta e}$ with the versions of the choice questions. In the second version, the attribute of location only included "in your county". Therefore, we retained only the "in your county" data for analyzing. Compared to Equation (10), this section also removed the location attribute S_{ik}^{loca} from the analysis.

3.3. Hypothesis Tests

We formulated statistically testable hypothesis based on a likelihood ratio (LR) test to examine whether marginal utility parameters are significantly different. For **Objective 1**, we aimed to assess the relative value of water quality investments in sites that are heavily degraded versus sites that are only moderately degraded and have the potential to produce a substantial set of ecosystem services. We proposed two hypotheses:

Hypothesis 1: Individuals hold the same value of water quality improvement in relation to ecosystem service and biological condition with different extents of degradation.

$$H_0: \beta_1^{\Delta H} = \beta_2^{\Delta H} = \ldots ; \beta_1^{\Delta E} = \beta_2^{\Delta E} = \ldots$$

Hypothesis 2: Individuals hold the same value of water quality improvement in relation to ecosystem service and biological condition with different current levels.

$$H_0: \beta_{\text{Inte1}}^{\Delta H} = \beta_{\text{Inte2}}^{\Delta H} = \ldots ; \beta_{\text{Inte1}}^{\Delta E} = \beta_{\text{Inte2}}^{\Delta E} = \ldots$$

It is recognized that heavily degraded sites may necessitate significant restoration efforts to attain sufficient ecological structure, functionality, and quality required for the provision of ecosystem services at their full potential. Conversely, moderately degraded sites may still provide a range of ecosystem services, but they face the possibility of future deterioration (Scheffer et al. 2001, 2009; Andersen et al. 2009). In light of this understanding, we suggested rejecting both hypotheses. Firstly, we implied that residents inhabiting the main study sites will assign varying levels of importance to a defined enhancement in water quality, depending on the extent of degradation observed in those sites. Secondly, we implied that individuals would place a higher value on averting further degradation in moderately degraded sites compared to a similar level of restoration in heavily degraded sites.

Regarding **Objective 2**, we planned to measure the impact of water stream location (within the county, upstream, downstream, or disconnected) on the perceived value of water quality and ecosystem restoration. To test this, we have proposed **Hypothesis 3**: Individuals hold equal value to the improvement of water quality, irrespective of the location of the water streams.

$$H_0: a_1^{loca} = a_2^{loca} = \cdots = 0$$

Economists have shown interest in the asymmetric dynamics between upstream and downstream water users, whereby downstream uses had little to no impact on upstream users, while upstream uses caused significant downstream impacts (van der Zaag 2007). In light of this understanding, our belief was that hypothesis 3 would be rejected, and individuals prioritize the improvement of their local water quality the most, followed by upstream areas due to the indirect effect on local water quality. However, they could be less concern regarding downstream and disconnected water quality improvement.

For **Objective 3**, our goal was to evaluate how the value of water quality and ecosystem restoration is affected by the economic and ecosystem context. Along the gradient of local economic and ecosystem character, residents may perceive water quality in different ways. Some may view it as a positive contributor to the local economy, particularly in terms of job opportunities related to recreation or aesthetic value. On the other hand, there may be a perception that regulations aimed at improving water quality negatively impact the local economy by restricting jobs in industries that generate pollution. Of course, improvements in water quality that balance marginal benefits and costs would be of net positive value to the local economy and environment. Nevertheless, the placement of a community on a spectrum that gauges the ecological level, as well as the degree to which the local economy relies on industries that adversely affect water quality, may influence residents' perceptions, their environmental attitudes, and therefore their valuation of in situ water quality benefits. In light of these understanding, our belief was that the following three hypotheses would be rejected:

Hypothesis 4: Individuals with different subjective perceptions of water pollution and pollution contribution hold the same value of water quality investments and stream ecosystem restoration.

$$H_0: a_1^{per} = a_2^{per} = \cdots = 0$$

Hypothesis 5: Individuals with different environmental attitudes toward water pollution hold the same value of water quality investments and stream ecosystem restoration.

$$H_0: a_1^{att} = a_2^{att} = \cdots = 0$$

Hypothesis 6: Individuals hold the same value in sites with different local economic contexts; ecosystem/degradation contexts; and the context of where the streams are relative to current and past economic activity, especially jobs in pollution-intensive industries versus other employment.

$$H_0: a^{SE} = 0, a^{EI} = 0, a^{PE} = 0$$

In addition, we also tested the potential impact of the real or hypothetical water quality baseline scenario presented in the choice questions on the perceived value of water quality and ecosystem service improvement.

4. Preliminary Results (Basic Results)

The responses from the seven-point Likert scale questions, followed the choice questions, provide qualitative evidence regarding respondents' understanding toward water quality attributes. Almost 70% of respondents voted as if their households would face the costs shown in the choice questions, and 67% of respondents voted as if the programs would achieve the projected results within 10 years. More than half (55%) of the respondents would vote differently if the programs took longer to achieve the results than stated in the choice scenarios. In addition, 65% of the respondents thought the attribute levels presented in this survey were within reasonable bounds. In general, respondents understood the design of the choice experiment and responded to survey carefully after deliberating considerations. Around 55% of our respondents considered it important to improve the water quality in their area, regardless of the costs, and 46% of the respondents thought their use of water bodies has been affected because of water quality degradations. The qualitative evidence suggests that most respondents recognize the value of water quality and ecosystem service improvement, and they also support water quality and ecosystem service improvement even when such actions can be economically costly.

4.1. Conditional Logit Model Results

By employing the choice experiment, we were able to investigate tradeoffs that respondents were willing to make among attributes associated with different levels of water quality improvement and cost. Respondents' choices were analyzed using a conditional logit model and the results were presented in Table 5. In Column of Table 5, we included only the status quo dummy variable, the water quality attribute levels, and cost. Then we expanded the analysis to incorporate a range of demographic variables in Column 2, including age, gender, race, income, and education. Building upon the findings in Column 2, Column 3 introduced county fixed effect. Furthermore, Columns 4 and 5 incorporated interactions between the baseline level and the changes in the Human Use Index and Ecological Integrity Index, respectively.

The coefficient for the Status Quo in Table 5, Column 1, was negative and statistically significant, suggesting a general preference for policy options over maintaining the current state.

This preference remained significant even after considering demographic variables and county fixed effects, although the significance level decreased from 1% to 10%. These results were consistent with the findings of Moore et al. (2018). The attitude question indicated that 72% of respondents were either neutral or expressed distrust regarding the government's proper use of tax money. This aspect might explain the reduced significance when individual characteristics were accounted for.

4.1.1. Ecosystem Service

Initially, we examined how individuals perceived the value of ecosystem services associated with improvements in water quality. To assess this, we utilized five Human Use Indices: Unusable to Boatable, Unusable to Fishable, Boatable to Fishable, Boatable to Swimmable, and Fishable to Swimmable. In Table 5, Columns 1 to 3, survey respondents demonstrated a positive utility for changing moderately degraded water quality but had a negative perception of enhancing severely degraded water. However, it is worth noting that none of these coefficients exhibited statistical significance, even after taking demographic variables and county fixed effects into account.

This led us to consider the variation in the status quo across different sites or water bodies when evaluating the value of a specific water quality change. To explore potential preference differences under various status quo conditions, we introduced an interaction between the status quo level and changes in the human use index. We employed different strategies to define the current level of human use, including (1) using the average score and (2) employing rank classification, including high, middle, and low levels of current water quality.

The findings revealed that people's assessment of the value of improving ecosystem services related to water quality was non-linear. In Table 5, Column 4, the results demonstrated that a higher current average score of the human use index was associated with a greater value of the improvements in ecosystem services. However, there was one exception with a negative significance observed for the change from Unusable to Fishable. When using the rank classification to define the current level (Table 5, Column 5), the results indicated that respondents assigned different values to the enhancement of ecosystem services based on the current water quality level. Specifically, when compared to the baseline of the lowest level of water quality, respondents attributed significantly higher value to Unusable to Boatable, Boatable to Fishable, and Boatable to Swimmable when the water quality was at a middle level. However, they only attributed significantly higher value to Unusable to Boatable when the water quality was at the highest level, with no significant differences observed for other improvements.

4.1.2. Biological Condition

Next, we utilized the Biological Condition Gradient (BCG) to evaluate the non-use benefits perceived by respondents in relation to water bodies, primarily focusing on species abundance, diversity, and overall ecosystem services. The BCG is regarded as a common assessment tool independent of individual physical, chemical or biological assessments of water bodies (Davies and Jackson 2006). Like Human Use Index, the BCG improvement in our study was categorized into five categories: “None or few” species to “Some” species, “None or few” species to “Many” species, “Some” species to “Many” species, “Some” species to “Most or all” species, and “Many” species to “Most or all” species.

In Table 5, specifically in Columns 1 to 3, the utility of respondents showed a significant increase at the 1% level when the biological condition gradient improved from "some" or "many" species to "most or all" species in the water bodies. Interestingly, the findings revealed that when the biological condition transitions from "None or few" species, the respondents significantly reduced their utility. This result of non-use benefit was aligned with the use benefit, as well as the previous studies suggesting that ecosystem change is discontinuous (Scheffer et al. 2001; Vandermeer and Yodzis 1999; Carpenter, Ludwig, and Brock 1999). As a result, the investments in moderately instead of severely degraded water bodies return larger increments in biological condition related to water quality.

We also employed the same strategies to examine potential differences in preferences across various status quo levels of biological conditions by introducing an interaction between the current level and changes in the BCG index. In Table 5, Column 4, the results indicated that a higher current average score of the BCG index was significantly associated with a lower value for improvements in BCG when transitioning from "none or few" to "many" species, but no significant association was observed for other categories. Additionally, when using rank classification to define the current level (Table 5, Column 5), the findings once again revealed that respondents assigned different values to the enhancement of biological condition based on the current level. More specifically, compared to the baseline of the lowest biological condition level, respondents attributed a significantly lower value to the transition from "none or few" species to "many" species and from "some" species to "most or all" species when the current biological condition was at a middle level. They also attributed a significantly lower value to the transition from "none or few" species to "some" species and from "some" species to "most or all" species when the current biological condition was at the highest level. However, they assigned a significantly higher value to the transition from "some" species to "many" species when the water quality was at the highest level.

4.1.3. Location

Table 5 also presented empirical evidence of the variation in individuals' marginal utility based on the location of water bodies. The interaction of location variables with the status quo indicator (SQ) revealed differences between water bodies within and outside respondents' counties. Generally, respondents derived the highest utility from maintaining the status quo in disconnected water bodies, with a significant difference from the location "in your county" at the 1% level. This was followed by downstream, which exhibited a significant difference from the location "in your county" at the 5% level in Columns 1 to 3, and the 1% level in Columns 4 and 5. Subsequently, utility was lower for water bodies maintaining the status quo within the county, and lowest for upstream, which demonstrated a significant difference from the location "in your county" at the 5% level in Columns 1 to 3, but not significant in Columns 4 and 5. By summarizing the coefficients of the status quo indicator (SQ) and the interaction of location variables with the status quo indicator (SQ), we observed the direction of marginal utility for maintaining the status quo across all location attributes. In Columns 3 and 4, respondents displayed a negative marginal utility for maintaining the status quo across all location attributes, whereas in Column 5, they exhibited a positive utility for Disconnected and Downstream. These results aligned with expectations and intuition, as individuals tended to be less concerned about locations that had no direct or indirect impact on their local water quality, hence preferring to maintain the status quo in those places. However, the significance of upstream and local water quality improvement was higher for individuals, as it has an indirect and direct impact on their water quality in comparison to downstream and disconnected water bodies. Consequently, they expressed more negative utility when it comes to maintaining the status quo in those locations.

4.1.4. Local Economic and Ecosystem Context

Furthermore, the findings indicated that we cannot reject the hypothesis of homogeneous preference concerning environmental attitudes and subjective perceptions of water pollution and pollution contribution. This result remains robust across different specifications. When examining the three indices created for each county - Socio-Economic, Ecological Integrity, and Pollution Economy - it was observed that individuals did not hold different values in sites with

Table 5. Conditional Logit Model with different specification.

	Simple	Eq (9)	Eq (9)	Eq (10) Average	Eq (10) Classification
Human_Swimmable & Fishable & Boatable	0.003	0.004	0.003	-0.074*	-0.005
	(0.025)	(0.025)	(0.025)	(0.041)	(0.083)
Human_Fishable & Boatable	0.029	0.029	0.028	0.027	0.071
	(0.026)	(0.026)	(0.026)	(0.028)	(0.073)
Human_Boatable	-0.002	-0.003	-0.003	-0.073*	-0.000
	(0.028)	(0.028)	(0.029)	(0.041)	(0.073)
Human_Unusable (omitted baseline)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Human_Fishable to Swimmable (Level 3 to Level 4)	0.045	0.043	0.043	0.016	0.065
	(0.032)	(0.032)	(0.032)	(0.052)	(0.045)
Human_Boatable to Swimmable (Level 2 to Level 4)	0.017	0.017	0.016	0.000	0.039
	(0.024)	(0.024)	(0.024)	(0.038)	(0.033)
Human_Boatable to Fishable (Level 2 to Level 3)	-0.022	-0.022	-0.022	-0.166***	-0.074***
	(0.015)	(0.015)	(0.015)	(0.044)	(0.020)
Human_Unusable to Fishable (Level 1 to Level 3)	-0.006	-0.005	-0.005	0.163***	-0.032
	(0.026)	(0.026)	(0.026)	(0.051)	(0.077)
Human_Unusable to Boatable (Level 1 to Level 2)	-0.014	-0.013	-0.012	-0.059	-0.052
	(0.028)	(0.028)	(0.028)	(0.045)	(0.073)
Eco_Most or all species	-0.093	-0.097	-0.097	-0.184***	-0.116
	(0.062)	(0.062)	(0.062)	(0.068)	(0.087)
Eco_Many species	0.113***	0.114***	0.114***	0.031	-0.083*
	(0.034)	(0.034)	(0.034)	(0.041)	(0.046)
Eco_Some species	0.144**	0.145**	0.144**	0.009	-0.179*
	(0.073)	(0.073)	(0.073)	(0.094)	(0.106)
Eco_None or few species (omitted baseline)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Eco_Many species to Most or all species (Level 3 to Level 4)	0.219***	0.224***	0.224***	0.226***	0.047
	(0.064)	(0.064)	(0.064)	(0.071)	(0.086)
Eco_Some species to most or all species (Level 2 to Level 4)	0.247***	0.252***	0.251***	0.181***	-0.053
	(0.054)	(0.054)	(0.054)	(0.067)	(0.071)
Eco_Some species to many species (Level 2 to Level 3)	0.046	0.046	0.046	-0.006	-0.064
	(0.051)	(0.051)	(0.051)	(0.070)	(0.072)

Eco_None or few species to Many species (Level 1 to Level 3)	-0.141***	-0.141***	-0.141***	0.121**	0.096**
	(0.034)	(0.034)	(0.034)	(0.052)	(0.047)
Eco_None or few species to Some species (Level 1 to Level 2)	-0.142**	-0.142**	-0.142*	0.004	0.198*
	(0.072)	(0.072)	(0.072)	(0.099)	(0.106)
Cost	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1.Status Quo	-0.714***	-0.337	-0.491*	-0.499*	-0.255
	(0.082)	(0.229)	(0.263)	(0.269)	(0.293)
1.SQ#In the County	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
1.SQ#Disconnected	0.336***	0.331***	0.335***	0.372***	0.467***
	(0.076)	(0.076)	(0.076)	(0.082)	(0.104)
1.SQ#Upstream	-0.140**	-0.148**	-0.151**	-0.035	0.010
	(0.069)	(0.069)	(0.070)	(0.075)	(0.082)
1.SQ#Downstream	0.154**	0.154**	0.153**	0.254***	0.523***
	(0.069)	(0.069)	(0.069)	(0.078)	(0.087)
1.SQ#c.Pro Conservation		-0.044**	-0.012	-0.010	-0.010
		(0.017)	(0.019)	(0.019)	(0.019)
1.SQ#c.None Government Trust		-0.006	-0.007	-0.006	-0.008
		(0.019)	(0.019)	(0.019)	(0.019)
1.SQ#c.Pro Tax Policy		0.000	0.003	0.001	0.001
		(0.021)	(0.021)	(0.021)	(0.021)
1.SQ#c.pollupercep		0.006	-0.002	-0.004	-0.005
		(0.018)	(0.018)	(0.018)	(0.018)
1.SQ#c.contripercep		-0.002	-0.002	-0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)
1.SQ#c.socio_econ_index_std		0.067**	0.001	-0.011	-0.012
		(0.028)	(0.142)	(0.143)	(0.143)
1.SQ#c.aquatic_index_std		0.152***	0.432***	0.446***	0.444***
		(0.020)	(0.116)	(0.117)	(0.117)
1.SQ#c.pollution_economy_index_std		-0.035	-0.231**	-0.231**	-0.229**
		(0.025)	(0.112)	(0.113)	(0.113)
c.Eco_MtoA#c.EcoAve				0.000	

	(0.000)	
c.Eco_NtoM#c.EcoAve	-0.006***	
	(0.001)	
c.Eco_NtoS#c.EcoAve	-0.000	
	(0.001)	
c.Eco_StoA#c.EcoAve	0.001	
	(0.001)	
c.Eco_StoM#c.EcoAve	0.000	
	(0.001)	
c.Human_BtoF#c.HummanAve	0.002***	
	(0.001)	
c.Human_BtoS#c.HummanAve	0.001*	
	(0.001)	
c.Human_FtoS#c.HummanAve	0.002***	
	(0.001)	
c.Human_UtoB#c.HummanAve	0.004***	
	(0.001)	
c.Human_UtoF#c.HummanAve	-0.006***	
	(0.001)	
2.EcoLel#c.Eco_MtoA		0.028
		(0.020)
3.EcoLel#c.Eco_MtoA		0.031
		(0.019)
2.EcoLel#c.Eco_NtoM		-0.195***
		(0.033)
3.EcoLel#c.Eco_NtoM		0.333
		(0.216)
2.EcoLel#c.Eco_NtoS		0.013
		(0.011)
3.EcoLel#c.Eco_NtoS		-0.136*
		(0.074)
2.EcoLel#c.Eco_StoA		-0.028*
		(0.016)
3.EcoLel#c.Eco_StoA		-0.587***
		(0.109)
2.EcoLel#c.Eco_StoM		0.012

					(0.010)
3.EcoLel#c.Eco_StoM					0.174***
					(0.037)
2.HummanLel#c.Human_BtoF					0.020***
					(0.008)
3.HummanLel#c.Human_BtoF					-0.011
					(0.024)
2.HummanLel#c.Human_BtoS					0.100***
					(0.025)
3.HummanLel#c.Human_BtoS					-0.034
					(0.063)
2.HummanLel#c.Human_FtoS					-0.007
					(0.030)
3.HummanLel#c.Human_FtoS					0.008
					(0.032)
2.HummanLel#c.Human_UtoB					0.073***
					(0.013)
3.HummanLel#c.Human_UtoB					0.299***
					(0.091)
2.HummanLel#c.Human_UtoF					-0.104***
					(0.023)
3.HummanLel#c.Human_UtoF					0.013
					(0.222)
	N	Y	Y	Y	Y
County Fixed Effect	N	N	Y	Y	Y
CE Version	1	1	1	1	1
N	37971	37971	37971	37971	37971

varying Socio-Economic indices after incorporating county fixed effects. However, when analyzing the interaction between Ecological Integrity and the status quo indicator (SQ), differences emerged among counties with different Ecological Integrity Indices. Respondents assigned a 1% significantly higher value to maintaining the status quo in counties with a higher Ecological Integrity Index. Additionally, respondents from counties with higher levels of polluted economic activity, particularly jobs in pollution-intensive industries, assigned a 5% significantly lower value to maintaining the status quo compared to individuals from other types of employment and counties with lower levels of pollution. This indicates that the perception of value in maintaining the current state varies among individuals based on the local economic and ecosystem context.

4.2. Hypothesis Tests

To further test our hypotheses and gain a clearer understanding of people's benefit in terms of use value and non-use value of water bodies, we conducted a series of likelihood ratio (LR) tests. These tests, combined with the estimated coefficients, allowed us to examine our hypotheses, assess trade-offs, and determine relative values among different attribute levels. The LR test results presented in Table 6 were consistent with our earlier descriptions and remained robust across different specifications.

Specifically, we rejected **Hypothesis 1** where individuals hold the same value of water quality improvement in relation to ecosystem service and biological condition with different extents of degradation. While there was weak statistical significance (at the 10% level) in the value assigned to the improvement of ecosystem services, we identified significant differences in respondent preferences for the improvement of the biological condition (at the 1% level).

For **Hypothesis 2,** when we used the average score to define the current level of ecosystem service and biological condition, we were unable to reject the null hypothesis that individuals attribute the same value to water quality improvement in relation to ecosystem service for different current levels. However, significant differences were detected among our respondents in their preference for improving the biological condition at different current levels (at the 1% level of significance). When we employed a rank classification to define the current level, the results in Table 6 indicated that respondents' values varied depending on the level of current water quality. Hypothesis 2 was rejected for both ecosystem service and biological condition when the baseline level was moderate, but it could not be rejected for either when the baseline level was high. When the baseline level was low, we rejected the null hypothesis that individuals attribute the same value to water quality improvement in relation to ecosystem service at the 1% significant level, but we couldn't reject it in relation to the biological condition.

Table 6. Likelihood-ratio Test results for Hypotheses.

Hypothesis	Null hypothesis	Specification		$\chi^2(df)$	p value	Reject Null
1	$\beta_1^{\Delta H} = \beta_2^{\Delta H} =...$ $\beta_1^{\Delta E} = \beta_2^{\Delta E} =...$	No interaction		2.96	0.0855	Yes
				20.08	0.0000	Yes
2	$\beta_{inte1}^{\Delta H} = \beta_{inte2}^{\Delta H} =...$ $\beta_{inte1}^{\Delta E} = \beta_{inte2}^{\Delta E} =...$	Average		0.67	0.4133	No
				23.55	0.0000	Yes
		Classification	Low	7.59	0.0059	Yes
				0.24	0.6236	No
			Middle	8.65	0.0033	Yes
				28.63	0.0000	Yes
			High	0.13	0.7216	No
				1.85	0.1739	No
3	$a_1^{loca} = a_2^{loca} =...=0$	Average		30.11	0.0000	Yes
		Classification		56.83	0.0000	Yes
4	$a_1^{per} = a_2^{per} =...=0$	Average		0.73	0.6938	No
		Classification		0.77	0.6819	No
5	$a_1^{att} = a_z^{att} =...=0$	Average		0.42	0.9358	No
		Classification		0.48	0.9239	No
6	$a^{SE} = a^{EU} = a^{PE} = 0$	Average		54.13	0.0000	Yes
		Classification		53.33	0.0000	Yes
7	$\beta_{inte\ version}^{\Delta \boldsymbol{H}} = \beta_{inte\ version}^{\Delta \boldsymbol{E}} =...=0$	Interaction with Version		33.23	0.0000	Yes

We rejected **Hypothesis 3** and **Hypothesis 6** at the 1% significance level, as detailed in the last section. However, based on our data, respondents' subjective perceptions of water pollution and pollution contribution, as well as their environmental attitudes, did not significantly affect their value of water quality improvement. Therefore, we could not.reject the **Hypothesis 4** and **Hypothesis 5**.

5. Conclusions and Policy Implications

This paper focused on the valuation of water quality in relation to ecosystem services and biological condition, utilizing a large-scale choice experiment conducted in the Northeast U.S. The analysis yielded three key sets of findings. Firstly, we observed that respondents assigned higher value to investments in moderately degraded water bodies compared to severely degraded ones, taking into account both ecosystem services and biological condition. Moreover, the value placed on such investments exhibited heterogeneity across different levels of the status quo. Secondly, our results provided empirical evidence that respondents derived the highest utility from maintaining the status quo in disconnected water bodies, followed by downstream, then in the county, and the lowest upstream. Lastly, the results showed that homogeneous preference could not be rejected for environmental attitudes and subjective perceptions of water pollution and pollution contribution. However, individuals held different values in sites with different local economic contexts and ecosystem contexts.

Our findings carry significant policy implications. Firstly, we explicitly consider the biophysical degradation and local-economic context across a wide range of primary study sites, allowing us to assess the potential for higher returns on water quality investment across numerous communities in the Northeastern U.S. This comprehensive approach enables a thorough evaluation of the likelihood of increased value associated with water quality improvement. Secondly, by incorporating the biological condition gradient alongside the water quality ladder at each site, we establish a more precise correlation that encompasses a spectrum of values, including both use and non-use values. This approach aligns with previous research (Keeler et al. 2012; EPA 2014; Van Houtven et al. 2014)and enables a more comprehensive assessment of the benefits derived from ecosystem services and non-use improvements linked to water quality. Our results indicate that people assign varying degrees of value to these aspects, offering valuable guidance for policymakers regarding the segments they should prioritize when implementing policies and investments for water quality enhancement. Additionally, our survey and sample selection methodology can facilitate benefit transfer estimates within a unified survey framework. The preference functions identified in this study can be further calibrated for valuation estimation when combined with an environmental attitude and socio-economic context survey.

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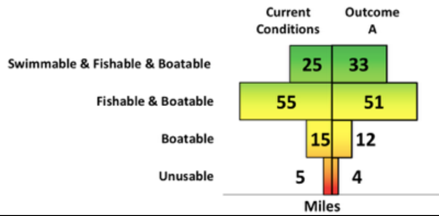
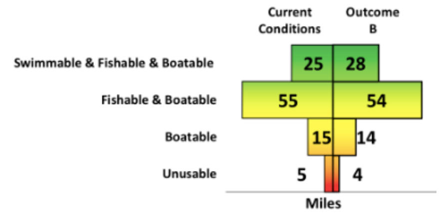
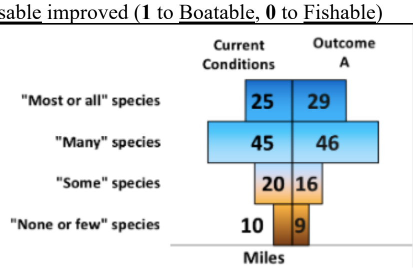
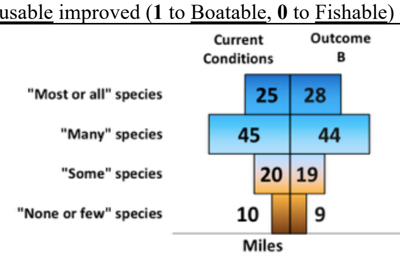
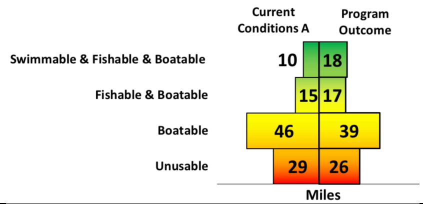
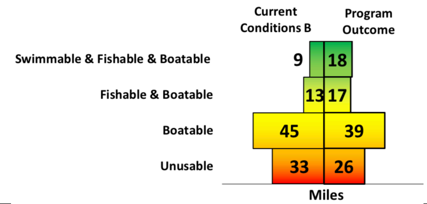
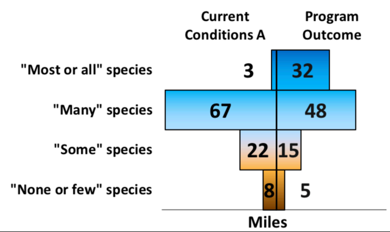
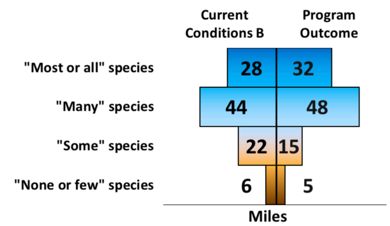
7. Appendix

Appendix A. Example of choice question based on current conditions.

	Produce Outcome A	**Produce Outcome B**
Location	**In your county**	
Miles rated by Human Use Score		
What changed	**8mi** Fishable improved to Swimmable **4mi** Boatable improved (**4** to Fishable, **0** to Swimmable) **1mi** Unusable improved (**1** to Boatable, **0** to Fishable)	**3mi** Fishable improved to Swimmable **2mi** Boatable improved (**2** to Fishable, 0 to Swimmable) **1mi** Unusable improved (**1** to Boatable, **0** to Fishable)
Miles rated by Ecological Integrity Score		
What changed	**3mi** "Many" improved to "Most or all" **5mi** "Some" improved (**4** to "Many", **1** to "Most or all") **1 mi** "None or Few" improved (**1** to "Some", **0** to "Many")	**3mi** "Many" improved to "Most or all" **2mi** "Some" improved (**2** to "Many", **0** to "Most or all") **1mi** "None or Few" improved (**1** to "Some", **0** to "Many")
Your annual Cost	**$300/yr for 10 years**	**$500/yr for 10 years**

- ○ **No Action:** 0/yr for 10 years
- ○ **Produce Outcome A:** $300/yr for 10 years
- ○ **Produce Outcome B:** $500/yr for 10 years

Appendix B. Example of choice question based on hypothetical conditions.

	Improve Conditions A	**Improve Conditions B**
Location	**In your county**	
Miles rated by Human Use Score		
What changed	**3mi** Fishable improved to Swimmable **10mi** Boatable improved (**5** to Fishable, **5** to Swimmable) **3mi** Unusable improved (**3** to Boatable, **0** to Fishable)	**9mi** Fishable improved to Swimmable **10mi** Boatable improved (**10** to Fishable, **0** to Swimmable) **7mi** Unusable improved (**4** to Boatable, **3** to Fishable)
Miles rated by Ecological Integrity Score		
What changed	**24mi** "Many" improved to "Most or all" **8mi** "Some" improved (**3** to "Many", **5** to "Most or all") **3 mi** "None or Few" improved (**1** to "Some", **2** to "Many")	**2mi** "Many" improved to "Most or all" **8mi** "Some" improved (**6** to "Many", **2** to "Most or all") **1mi** "None or Few" improved (**1** to "Some", **0** to "Many")
Your annual Cost	**$40/yr for 10 years**	**$250/yr for 10 years**

- ○ **No Action:** 0/yr for 10 years
- ○ **Improve Conditions A:** $40/yr for 10 years
- ○ **Improve Conditions B:** $250/yr for 10 years