Cyanobacterial Concentrations Cause Significant Welfare Declines to Recreational Fisheries: Evidence From a Bloom-Prone Urban Lake[⋆,⋆⋆]

Jordan W. Smith[a,*], Chase C. Lamborn[a]

[a] *Institute of Outdoor Recreation and Tourism, Department of Environment and Society, S. J. & Jessie E. Quinney College of Agriculture and Natural Resources, Utah State University, 5215 Old Main Hill, Logan, 84322, Utah, USA*

ARTICLE INFO

Keywords:
chlorophyll-*a*
aesthetic threshold
photo-elicitation
random-effects ordered probit
travel cost method
gradient-boosted decision trees
water quality index

Abstract

Chlorophyll-*a* is widely monitored as an indicator of bloom conditions, yet managers often lack a defensible way to translate sporadic measurements into decision-relevant recreation outcomes. We develop and demonstrate a replicable, threshold-based indicator-to-outcome workflow for bloom-prone fisheries. During 27 site-days in 2022, we intercepted 384 visitors; 290 completed surveys (75.5% response rate), of which 174 anglers formed the analytic sample. Anglers provided repeated photo-based ratings of water suitability for fishing; random-effects ordered probit models were used to estimate a user-defined aesthetic threshold and to convert chl-*a* into a perceived quality index. Next, we built a daily lake-wide chl-*a* time series for 2022 to bridge temporal data gaps in irregular in-situ observations. This was done by training a histogram gradient-boosting model that captured the temporal structure of chl-*a* concentrations, supporting use as an operational daily indicator under sparse sampling. Predicted chl-*a* exceeded the angler-defined threshold (58.3 μg/L) on 83 days of the year, including a 35-day stretch during peak summer demand. We then embedded the quality index in a single-site negative binomial travel cost model to estimate welfare and translate indicator exceedances into outcome losses. The estimated consumer surplus was $85.42 per trip, and counterfactual welfare calculations indicate that keeping daily chl-*a* below the threshold would have increased total angling trips and raised annual surplus from $10.1 million to $16.2 million, implying a welfare loss of $6.0 million in 2022. The workflow illustrates how monitored biophysical indicators can be recast as threshold-triggered, stakeholder-relevant outcome metrics to support risk communication and adaptive management.

1. Introduction

Freshwater harmful algal blooms (HABs), driven in large part by nutrient enrichment and climate variability, are increasing in frequency and severity globally, with well-documented implications for aquatic ecosystem function, public health, and recreational access [1]. Yet persistent gaps remain in assessing the relationship between the biophysical proxies of bloom conditions—particularly chlorophyll-*a* (chl-*a*) and turbidity—and human welfare [2]. This gap is especially consequential for anglers, who are frequent users of bloom-prone systems and may adjust behavior based on perceived conditions even in the absence of formal advisories [3, 4].

Threshold-based workflows offer a practical pathway for closing this gap because recreationists often respond nonlinearly to changes in "optical water quality"—the visual appearance of water that shapes immediate judgments of suitability [5, 6, 7]. This growing literature shows that perceived recreational quality can shift sharply once water crosses an aesthetic threshold, beyond which the site is judged unappealing or unsafe. For lakes, these perceptions are commonly anchored in visible cues (e.g., clarity, greenness, scums) and can be quantified by linking subjective ratings to objective indicators such as chl-*a* [8, 9]. Importantly, threshold locations vary across systems and user expectations—particularly in optically complex waters where high background turbidity can obscure or mimic bloom signals—reinforcing the need for stakeholder- and context-specific thresholds that can support clearer risk communication and more defensible decision triggers [10].

This paper advances an integrated, replicable indicator-based workflow that translates sporadic chl-*a* monitoring into the decision-relevant outcome of economic welfare generated by a recreational fishery in a bloom-prone urban lake. First, we estimate stakeholder-defined aesthetic thresholds using a controlled photo-elicitation approach embedded in an on-site intercept survey of anglers, focusing on judgments relevant to fishing. Second, we use machine learning (histogram-based gradient boosting model) to transform irregular in situ observations into a continuous daily, lake-wide chl-*a* indicator series. Third, we operationalize the survey-derived threshold by constructing a perceived quality index that maps daily chl-*a* conditions into a form that can be

[⋆] This research was funded by the Utah Division of Water Quality and the Institute of Outdoor Recreation and Tourism at Utah State University. The author would like to acknowledge Anna Miller, for providing input into the study's survey instrument, Andrea Jacobs for conducting the on-site surveys, and D'yani Wood for assistance with color correcting lake photographs. A previous version of this paper was delivered at the American Fisheries Society Annual Conference in San Antonio, Texas (August, 2025).

[⋆⋆] The survey data collected from anglers contain human-subject information and are not publicly available. All other data used in this study, as well as the code required to reproduce the analyses, are available from the corresponding author upon reasonable request.

[*] Corresponding author

jordan.smith@usu.edu (J.W. Smith)

https://www.linkedin.com/in/jordan-smith-38351b35/ (J.W. Smith); chase.lamborn@usu.edu (C.C. Lamborn)

ORCID(s): 0000-0001-7036-4887 (J.W. Smith); 0000-0003-0854-6270 (C.C. Lamborn)

integrated into recreation demand modeling and interpreted in management terms. Fourth, we quantify welfare impacts by embedding the perceived quality index within a travel cost model and deriving consumer surplus and an annual welfare-loss attributable to threshold exceedance.

The manuscript makes four contributions that correspond to distinct indicator-development steps. First, we identify an angler-defined aesthetic threshold for "too green" conditions using photo-series data, addressing limited evidence on angler-specific perceptual thresholds [11, 12, 13]. Second, we generate a daily chl-*a* time series from sporadic monitoring using histogram-based gradient boosting, which adds to the growing literature on the use of machine learning methods to achieve the temporal resolution needed to link water quality data with human behavioral responses [14, 15, 16]. Third, we translate chl-*a* into a perceived quality index, creating the link necessary to translate thresholds to economic losses—a vital step to providing clear policy guidance [2]. Finally, we produce per-angler and aggregate welfare-loss indicators attributable to exceedance of the chl-*a* threshold, converting a familiar biophysical metric into a politically relevant, economically interpretable outcome for management appraisal. We next situate the research within the broader literature on aesthetic thresholds of water quality, travel cost valuation in recreational fisheries, machine learning for environmental monitoring, and the welfare impacts of environmental degradation.

2. Related Literature

2.1. Aesthetic Thresholds of Water Quality

People's visual perceptions of water quality play a critical role in recreational site choice and satisfaction. Numerous studies have demonstrated that lake users rely on cues like water clarity, color (greenness), and surface scums to judge if a waterbody is safe or appealing for recreation [10]. These perceptions often translate into specific "aesthetic thresholds" beyond which the water is deemed unsuitable for activities like swimming, boating, or fishing [5, 6, 7]. Researchers have quantified such thresholds by relating users' ratings of water quality to measured variables (e.g., Secchi depth, turbidity, chl-*a*) [5]. Chl-*a* concentration—a proxy for algal biomass and "greenness" of water—shows threshold effects in user perceptions, though the critical levels can vary. In relatively pristine settings, even modest algae levels can trigger negative reactions. Smeltzer and Heiskary [17] observed that around 8 μg/L chlorophyll-a was enough to cause frequent reports of use impairment in Lake Champlain (Vermont). This value falls within the low end of user-acceptable conditions, indicating a very low tolerance for algal greenness in that clear water lake. By contrast, in eutrophic or sediment-rich waters, people tolerate much higher algal concentrations before deeming the lake unsuitable. Surveys of Florida and Louisiana lakes, for instance, suggest that chlorophyll levels up to roughly 10–15 μg/L might still be considered only "slightly impaired" [5], and thresholds for "unacceptable" conditions have been reported on the order of 30+ μg/L in those regions [5]. In extreme cases, chl-*a* concentrations on the order of 50–80 μg/L are associated with recreation being virtually impossible or entirely unpleasant [5]. Overall, these studies indicate that a bloom turning the water visibly green will markedly degrade the aesthetic and recreational quality once it surpasses a certain concentration—often on the order of a few tens of micrograms per liter, depending on the waterbody's typical clarity. These aesthetic water quality thresholds have become important in management; they are used to inform numeric nutrient criteria and public advisory levels, ensuring that lakes intended for recreation remain below levels beyond which recreational activity becomes impaired [10]. In summary, there is a well-established literature showing that when water becomes "too green" or murky, recreationists respond negatively, and this tipping point can be quantified (often near 15–20 μg/L chl-*a* in many lakes, though higher in naturally turbid systems) [5]. Our study builds on this foundation by pinpointing the threshold specific to anglers at a chronically turbid, bloom-prone lake, and by doing so with a controlled photo-elicitation method to isolate purely visual preferences.

2.2. Travel Cost Models in Recreational Fisheries

Economic valuation of recreational fisheries has a rich history, with the travel cost method being one of the most widely used tools to quantify the consumer surplus (welfare) that anglers derive from fishing opportunities. In essence, the travel cost method infers the value of a recreational site by examining how far and how often people travel to visit it—travel distances and expenses serve as a proxy for price in revealing demand. Numerous studies around the world have applied the travel cost method to recreational fishing, establishing it as a standard approach to estimate per-trip and annual use values [18]. Johnston et al. [19], for example, conducted a meta-analysis of recreational fishing valuations and confirmed welfare estimates generated via the travel cost method vary with species sought, catch rates, site quality, and angler characteristics. The method has been employed in diverse contexts ranging from remote salmon rivers to urban fisheries. At the continental scale, the aggregate value of recreational fisheries is striking: a recent synthesis of European studies estimated a total annual value on the order of $9–11 billion USD for recreational fishing across European countries [20]. This figure reflects the enormous popularity of angling and the significant willingness-to-pay for access to quality fishing in Europe's lakes, rivers, and coastal waters. In the United States, likewise, recreational fisheries generate large economic benefits; for instance, the Great Lakes fishery alone has been valued at roughly $0.9 billion per year in consumer surplus for anglers, based on regional travel cost analyses [21]. Individual site studies further illustrate these values: in a restored Spanish estuary (Nerbioi), each fishing trip was valued at about €15, summing to over €1 million in annual benefits for that local fishery [22]. In high-demand trophy fisheries, per-trip values can soar much higher—one Irish study found international salmon anglers were willing to pay approximately €800+ for a single day of fishing in premier river reaches [23]. Such examples underscore that recreational fishing is not just a cherished pastime but also an economically significant activity. The travel cost literature also emphasizes the role of site attributes (e.g., environmental quality) in determining use value. Anglers exhibit preferences for better environmental conditions, which translate into higher site demand and value. Many studies using the travel cost method to value lake and stream fishing incorporate measures of water quality (clarity, pollution levels) or biological quality (catch rates, fish size) as key determinants of trip frequency. In so doing, researchers can estimate the marginal value of environmental improvements—for example, how much more an angler would be willing to pay (or how many more trips they would take) if water clarity improved or fish populations increased. Such integration of ecological factors into travel cost models has been demonstrated in Iowa's recreational lakes: Egan et al. [24] showed that anglers' lake visitation rates were significantly responsive to water quality metrics like Secchi depth (turbidity) and phosphorus levels, and they estimated positive willingness-to-pay for incremental improvements in these metrics. In summary, the travel cost method literature provides robust evidence that recreational fisheries contribute substantial welfare to society, and that this welfare is influenced by environmental conditions. These insights set the stage for our use of a travel cost model to quantify Utah Lake anglers' welfare, especially as it varies with water quality. By incorporating a quality index (based on anglers' aesthetic thresholds for the greenness of the water) into the demand model, our approach aligns with the established practice of linking site quality to economic value in recreation demand analyses.

2.3. Machine Learning for Environmental Monitoring

Advances in machine learning have increasingly been leveraged to address data gaps and prediction challenges in environmental monitoring. Traditional monitoring of water quality (e.g., periodic in situ sampling of chl-*a*, nutrients, etc.) often yields sparse datasets that miss temporal dynamics of phenomena like algal blooms. In response, researchers are turning to data-driven models that can assimilate diverse inputs—weather variables, remote sensing data, past observations—to provide more continuous and refined estimates of environmental indicators. In particular, tree-based ensemble methods such as random forests and gradient boosting have shown exceptional performance in predicting water quality variables [14, 15, 25, 16]. These algorithms can capture non-linear relationships and interactions between predictors without strong parametric assumptions, making them well-suited for complex ecological systems. For example, Savoy and Harvey [25] compiled water quality, meteorological, and watershed data for 82 rivers across the U.S. and applied an extreme gradient boosting model to predict daily chl-*a* concentrations in each river. Their continental-scale model achieved high accuracy in reproducing observed chlorophyll dynamics, even with only sparse sampling data available for training. Notably, the model identified turbidity and total nitrogen as the two most important predictors governing chl-*a* levels [25]—a result that aligns with limnological understanding that suspended sediments and nutrient availability strongly drive algal biomass. The use of a histogram-based gradient boosting algorithm (similar to the one we employ in our study) also allowed Savoy and Harvey to explore the trade-off between using in situ versus remote-sensed inputs. Interestingly, they found that a model fed only with universally available remote sensing estimates (like satellite-derived turbidity or watershed characteristics) could still achieve highly correlated chl-*a* predictions, with only a small bias penalty relative to using local field measurements [25]. This highlights the power of machine learning to fill in temporal gaps: even when direct chl-*a* readings are infrequent, a well-trained model can interpolate or forecast daily concentrations with useful accuracy by exploiting correlated signals (e.g., turbidity, flow, temperature, weather).

A broader body of work reinforces that machine learning approaches often outperform traditional statistical or process-based models in environmental prediction tasks. Recent reviews of harmful algal bloom forecasting conclude that machine learning-based models significantly improve predictive skill for bloom occurrence and intensity [26]. Complex, non-linear patterns in multivariate data (e.g., interactions between temperature, nutrients, and hydrology leading to a bloom) can be learned by algorithms such as gradient boosting, neural networks, and hybrid ensemble techniques. For instance, in one study of coastal algal blooms, researchers compared five different tree-based machine learning models and found gradient boosting regressor models to be among the most accurate for predicting chl-*a* in Hong Kong's waters [27]. Another study applied both a gradient boosting regressor model and a deep learning LSTM (Long Short-Term Memory network) to time-series of environmental data in order to predict algal bloom events and seasonal chl-*a* changes [28]. Both approaches yielded reliable forecasts, demonstrating the flexibility of machine learning to handle both tabular and sequence data in water quality contexts. A key advantage of these models is their ability to ingest diverse data streams—combining satellite imagery, meteorological forecasts, watershed land-use data, and point sensor readings, for example—to improve predictions. Moreover, emerging work in explainable AI is making it easier to interpret machine learning models, identifying which variables or patterns are most influential for predictions [26]. This is crucial for management uptake, as decision-makers need to understand the drivers (e.g., a spike in nutrients or a stretch of hot, calm weather) behind a model's bloom prediction. Overall, the integration of machine learning into environmental monitoring is enabling a shift from static, infrequent data points to continuous, high-resolution indicator estimates. By employing a histogram-based gradient boosting model in our study, we extend this paradigm to Utah Lake's chl-*a* dynamics—using machine learning to transform irregular field measurements into a daily time series of lake-wide algal concentrations. This approach is grounded in the successful application of similar models in water quality research and is expected to improve our ability to link water quality fluctuations with economic outcomes on a fine temporal scale.

2.4. Welfare Impacts of Environmental Degradation

Environmental degradation can translate directly into losses of human welfare. These losses may manifest through diminished recreational opportunities, health impacts, or declines in property values and ecosystem services. A substantial literature in environmental economics seeks to quantify the welfare costs of environmental decline, often in monetary terms, to inform policy and management. In the context of freshwater systems, eutrophication (the over-enrichment of waters with nutrients, leading to excessive algal growth and low water quality) has been identified as a costly problem on regional and global scales. Dodds et al. [29] provided one of the first comprehensive estimates of the economic damages of eutrophication in U.S. lakes and rivers, finding annual welfare losses on the order of $2.2 billion when considering multiple use sectors. Importantly, a large share of this cost was attributed to losses in recreational use of water bodies—over $1 billion per year in reduced welfare for boaters, swimmers, and anglers due to poor water quality [29]. Another substantial component was loss in waterfront property values (estimated at over $2 billion per year) as persistent algal blooms and murky water make lakes less desirable for homeowners [29]. These figures underline that the stakes are high: when a lake "goes green" with algae, it can both deter visitors (shrinking recreational enjoyment and tourism spending) and erode the value of real estate and local tax bases. Similar conclusions have been drawn in other countries—for example, studies in the UK and EU have tallied the cost of water quality degradation in terms of forgone recreational experiences and higher water treatment expenses, amounting to billions of euros across affected water bodies [30, 31].

Drilling down to specific scenarios, harmful algal bloom events—which involve rapid growth of cyanobacteria or algae that often produce toxins—can cause acute economic shocks. When blooms lead to beach closures, fishing bans, or health advisories, local businesses and communities can suffer immediate losses. NOAA's National Centers for Coastal Ocean Science estimate that, in the United States, harmful algal bloom events cost on average $10–100 million annually in aggregate, considering impacts to fisheries, tourism, and public health [2]. Individual severe bloom incidents have been documented to incur tens of millions in damages. For instance, a toxic cyanobacteria outbreak in 2014 that shut down drinking water in Toledo, Ohio, also kept recreational boaters and anglers off Lake Erie; the lost recreational spending from that single event was estimated between $10 and $12 million for the local economy (U.S. National Office of Harmful Algal Blooms, 2024). Similarly, on the marine side, blooms of *Karenia brevis* ("red tides") in Florida have caused beachgoers to stay away, leading to multi-million-dollar losses for coastal businesses in affected counties [32]. These case studies reinforce the point that environmental quality degradation has real and sizable welfare implications, often realized quickly in the recreation sector where users can respond by simply not showing up when conditions are poor. Even absent outright closures, chronic sub-par conditions (e.g., chronically high chl-*a* or frequent minor blooms) can gradually diminish the recreational value of a site. As noted earlier, recreation demand models detect lower visitation or lower willingness to pay at sites with degraded water clarity [24]. Over time, these behavioral shifts cumulate into large welfare losses when multiplied across the user population. Moreover, there can be a feedback loop: reduced recreation and tourism can lessen public support and funding for maintaining or improving the resource, potentially exacerbating the degradation.

From an ecosystem services perspective, the loss of recreational fishing quality due to algal blooms is a notable welfare cost that has drawn recent research attention. Studies of Midwestern US lakes found that frequent algal bloom advisories significantly reduced recreational fishing effort, translating into welfare losses for anglers that could be measured in lost consumer surplus per season [13, 33, 34]. Another recent analysis focused on the U.S. "Heartland" region estimated the economic losses specifically to inland recreational fisheries from water quality declines, including harmful algal bloom events [12]. The authors documented that poorer water clarity and bloom occurrences led to measurable drops in fishing license sales and trip numbers, indicating that anglers indeed curtailed their activities in response to environmental degradation (or substituted away to unaffected sites). Such behavioral changes imply welfare losses both at the individual level (loss of enjoyment) and the aggregate level (reduced economic activity in communities that rely on sportfishing). Notably, anglers may have distinct sensitivities compared to other recreationists; they might tolerate slightly greener water if fishing quality is good. However, when algal levels cross into a range that is harmful to fish health or causes unappealing conditions (odors, scums), even anglers' utility plummets—a dynamic our study specifically quantifies for Utah Lake. Overall, the literature clearly indicates that environmental degradation carries significant welfare costs, and quantifying these in monetary terms can help inform better management. By linking a water quality indicator (chl-*a*) to an economic valuation model (travel cost demand), our work follows a well-established interdisciplinary approach. It contributes to the global evidence base by providing an estimate of how much value is lost when a popular fishery experiences cyanobacteria concentrations above the level anglers consider acceptable. This kind of information is crucial for policy: it translates abstract water quality metrics into tangible social costs, thereby making a compelling case for investing in water quality improvement and bloom prevention as ecological and economic imperatives [29]. The confluence of recreation economics and environmental science in this study reflects the broader trend in ecological indicators research—moving beyond biophysical assessment to incorporate human dimensions and welfare outcomes as integral parts of ecosystem health indicators.

3. Methods

3.1. Study System and Decision Context

Utah Lake is a large, shallow, and slightly saline freshwater lake situated in central Utah, bordered by the rapidly urbanizing Provo-Orem metropolitan area (Figure 1). The lake spans approximately 380 km^2 and has a mean depth of less than three meters, making it particularly vulnerable to wind-driven sediment resuspension and nutrient cycling. Utah Lake's hydrology is influenced by both anthropogenic and natural factors. Its sole surface outflow is the Jordan River, which flows northward into the Great Salt Lake. However, over half of the lake's annual outflow is lost through evaporation, resulting in seasonal fluctuations in salinity and nutrient concentration [35].

Historically, the lake supported a diverse native fish assemblage, including 13 endemic species. Today, however, only two native species persist: the Utah sucker (*Catostomus ardens*) and the endangered June sucker (*Chasmistes liorus*), the latter of which is subject to active recovery efforts under the June Sucker Recovery Implementation Program [36]. The fish community is now dominated by common carp (*Cyprinus carpio*), an invasive species introduced in 1883, which currently constitutes more than 90% of the lake's total fish biomass [37]. This ecological shift, coupled with nutrient enrichment and increasing frequency of cyanobacterial blooms, has made Utah Lake a focal point for water quality and fisheries management in the region.

3.2. Eliciting Aesthetic Thresholds From Anglers

To assess anglers' perceptual thresholds for water quality, we employed a photo-based visual assessment technique. This approach aligns with guidance from the U.S. Environmental Protection Agency [38] and builds upon prior work in perceptual threshold research for aquatic recreation [5, 7]. A set of high-resolution photographs was obtained from the Utah Division of Water Quality (DWQ), taken at a variety of locations around the lake between June and September 2021. Each photograph was taken concurrently with in situ measurements of key water quality parameters, including chl-*a* and turbidity (measured in Nephelometric Turbidity Units [NTU]), among others.

We selected ten photographs—five representing open-water settings and five depicting shoreline areas. These images were chosen to capture a wide range of chl-*a* concentrations (from 9.7 to 406.7 μg/L) and turbidity levels (from 27.2 to 61.7 NTU), representative of typical and extreme summer conditions at Utah Lake. Photographs were edited to a uniform size and paired into sets showing visual differences in water clarity and color. To avoid cueing respondents, no numerical or textual water quality information was presented alongside the images. To enhance realism, photographs included both wide landscape perspectives and a downward-facing perspective with a white visual reference object in the foreground to provide consistent color scaling across lighting conditions. Pilot testing helped refine the final image set by excluding photographs that appeared artificially manipulated or contextually ambiguous. The final set of image pairs shown to respondents are displayed in Figure 2.

Respondents were randomly shown three of the five photo-pairs and asked to evaluate each pair based on their perceived desirability of the water for fishing at the depicted location. Each activity was rated on a 7-point Likert scale ranging from 1 (very undesirable) to 7 (very desirable), with 4 representing a neutral evaluation.

3.3. Covariates of Interest

In addition to the chl-*a* concentration and turbidity levels associated with each photo-pair, we included other questions in the survey to examine whether certain characteristics or prior experiences influenced how anglers evaluated the water's desirability for fishing. These covariates were selected based on existing literature suggesting water quality perceptions and recreation decisions are shaped not only by visual indicators, but also by familiarity with the resource, recreational history, and the value individuals place on their recreational experiences [5, 39, 4].

Respondents were asked how many times they had visited Utah Lake for recreation in the past 12 months. We hypothesized that higher visit frequency would be associated with greater tolerance of degraded water quality, potentially due to habituation or an increased attachment to the site. Frequent users may adapt to visual water quality conditions over time or be less deterred by poor visual cues due to established routines or familiarity with the lake's natural variability. This hypothesis aligns with prior research suggesting that long-term users of degraded water bodies may recalibrate their aesthetic expectations and recreational thresholds [3, 40].

Respondents also reported how many years they had been visiting Utah Lake. We posited that a longer history of recreational use may similarly be associated with increased tolerance to water quality impairments. However, it is also plausible that individuals with longer use histories may have substituted to other, less impaired sites over time if they perceived declining conditions—an idea consistent with theories of spatial substitution in recreational demand modeling [41]. Including this variable allows us to test for potential legacy effects of long-term exposure to suboptimal conditions.

To measure respondents' awareness of water quality problems, the survey asked whether they had ever experienced a water quality issue at Utah Lake (e.g., access point closures or bloom advisories) or were aware of such issues through signage or word of mouth. We expected that individuals with firsthand experience or heightened awareness of past water quality issues would exhibit lower

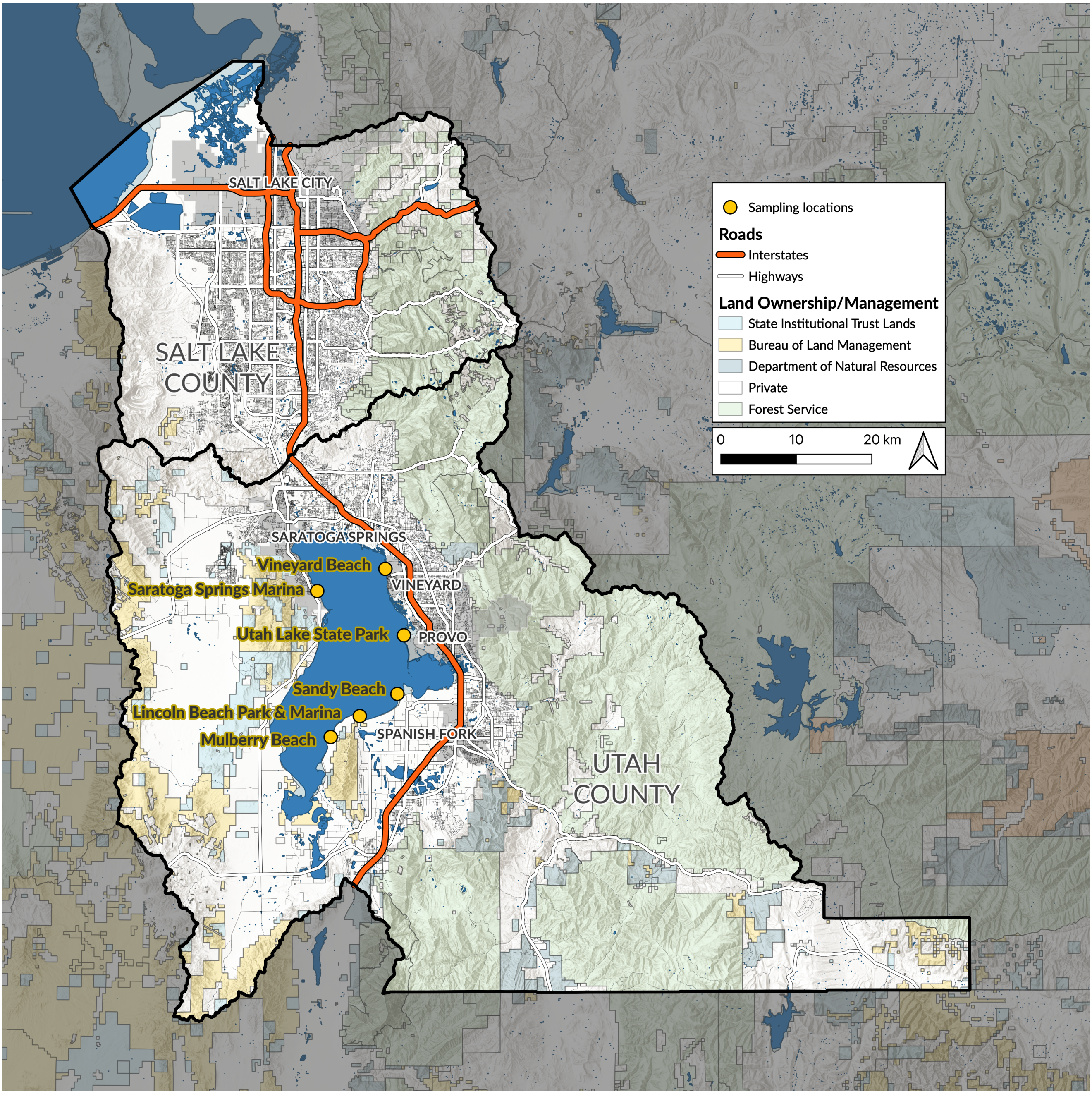

Figure 1: Utah Lake, Utah (USA) with Sampling Locations.

desirability ratings for the depicted conditions, especially when visual cues were ambiguous. Prior studies have shown that perceived water quality and risk assessments are influenced by both visible and non-visible information, including prior experiences and culturally shared environmental knowledge [4, 7]. Including this variable helps differentiate visual assessments made in isolation from those influenced by broader knowledge or past exposure to harmful algal bloom advisories.

The survey also asked about the respondent's gender given prior research suggesting that risk perceptions related to environmental quality often vary by gender [42]. Specifically, we hypothesized that men would exhibit higher tolerance for degraded water conditions than women, potentially leading to higher desirability ratings for fishing.

Lastly, we included a variable representing the respondent's travel cost to reach the lake on the day of the survey. This measure serves as a proxy for the fiscal use value of the recreation experience and is a commonly employed indicator in recreation demand studies [41]. We hypothesized that individuals incurring higher travel costs may hold higher expectations for water quality and may therefore be more critical of poor visual conditions. Conversely, higher travel

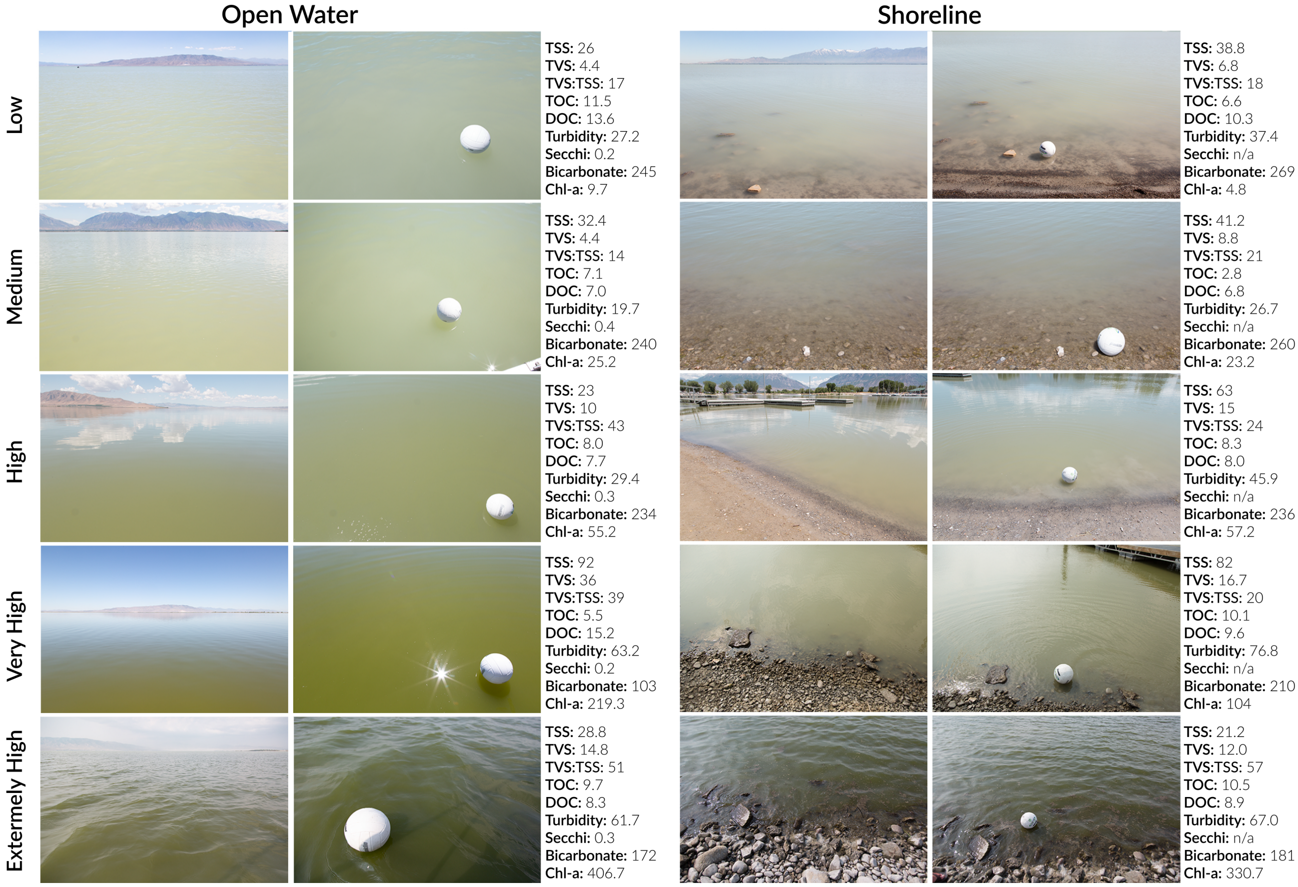

Figure 2: Image Pairs Shown to Anglers with Associated Water Quality/Clarity Data.

investment might also reflect stronger recreational commitment or lake-specific attachment, which could attenuate the influence of suboptimal water appearance. This covariate allows us to assess whether monetary or opportunity cost influences aesthetic judgments and perceived acceptability of water conditions.

Together, these covariates provide a richer understanding of how perceptual thresholds may vary across angler subgroups with different use patterns, experiences, and resource valuation. Including these variables in the analysis ensures responses to visual cues are interpreted within a broader behavioral and socio-economic context, thereby enhancing the robustness of our models and the applicability of our findings for lake management and risk communication.

3.4. Survey Data Collection

Data were collected through an on-site intercept survey administered during the summer of 2022. Six high-use access points were identified for data collection around Utah Lake (Figure 1). These survey locations were chosen in consultation with the Utah Lake Water Quality Study Steering Committee, ensuring geographic diversity and a mix of shoreline and boat-based fishing locations. Sampling occurred on weekends (Friday through Sunday) between noon and 8 pm to maximize intercept rates of active recreationists.

Survey technicians approached adult visitors and asked the member of each group with the most recent birthday to complete the survey (a widely used randomization technique to reduce selection bias). Respondents completed the survey on-site using a tablet with Qualtrics survey software installed; this allowed for randomized image presentation and standardized response recording. Respondents could indicate their preference to take the survey later if they provided the research technician with an email address. Participation was voluntary and anonymous, and all procedures were approved by the Utah State University Institutional Review Board (IRB #12806).

3.5. Survey Data Analysis

We began by calculating descriptive statistics to summarize respondents' ratings and demographic characteristics. To model the effect of visual water quality indicators on anglers' desirability ratings, we estimated a random-effects ordinal probit panel data model. This modeling framework accounts for repeated ratings by the same individual across multiple image pairs, thereby adjusting for respondent-level heterogeneity in response behavior. We let $y_{it} \in \{1, \dots, 7\}$ denote respondent i's rating for image-pair t. The latent utility formulation is

$$y_{it}^{*} = x_{it}\beta + u_i + \varepsilon_{it},$$

The covariate vector x_{it} includes chl-a, turbidity, the location of the photograph (open-water versus shoreline), and respondent-level controls (trip frequency, years of use, prior experience/awareness of water-quality issues, gender, and travel cost). Models were estimated by maximum likelihood in Stata 18 [43].

3.6. Translating chl-*a* Into a Quality Index

To translate anglers' survey responses into a perceived quality index q, we let c denote the chl-a (μg/L) corresponding to the images shown to anglers in the survey. From the ordered-probit model of perceived desirability, we define the probability that conditions are undesirable for angling as

$$P_u(c) \equiv \Pr(Y \in \{1, 2, 3\} \mid c),$$

where response categories 1, 2, and 3 are degrees of "undesirable." We define the perceived quality as

$$Q(c) \equiv 1 - P_u(c).$$

Estimates were generated using a purpose-built Stata routine. For a grid of chl-a values c (0–400 μg/L in 10-μg/L increments), the script uses Stata's `margins` with `predict(outcome(#))` to obtain the category probabilities $P_k(c) = \Pr(Y = k \mid c)$ for each of the seven ordered response categories k evaluated at the sample means of all non-chl-a covariates.

3.7. Constructing a Daily chl-*a* Indicator Series From Sporadic Data

Historical water-quality observations (including sampling dates and chl-a concentrations) were obtained from the Utah Lake Data Explorer [44]. Daily meteorological variables (precipitation, maximum temperature, mean temperature) corresponding to each sampling date and location were retrieved via the Meteostat Python library, which provides harmonized daily aggregates of data collected by the National Oceanic and Atmospheric Administration [45].

We modeled chl-a from the irregularly sampled in-situ observations using a contemporaneous weather and time-dependent structure. The data included sampling date t_i, chl-a concentration y_i, daily precipitation P_i (mm), maximum temperature $T_i^{\max}$ (°C), and mean temperature T_i^{mean} (°C). Records missing t_i or y_i were dropped. Our goal is to learn a function $F(x_i)$ that predicts y_i from features x_i constructed to respect the series' irregular timing, capture seasonal structure, and exploit short-run persistence without look-ahead.

3.7.1. *Feature Engineering (seasonality and irregularity)*

Because algae often follow seasonal cycles, we translated each date into where it sits in the year using two smooth "season" coordinates. This was done with Fourier terms using day-of-year d_i (1–366). For harmonic k (we used $K = 1$):

$$S_{ik} = \sin\left(\frac{2\pi k d_i}{365.5}\right), \qquad C_{ik} = \cos\left(\frac{2\pi k d_i}{365.5}\right)$$

Additionally, samples are not evenly spaced. The model addresses this with two additional features: how long it has been since the last sample (sampling irregularity), and what recent levels looked like—using only past information (persistence). Sampling irregularity and persistence were captured with:

$$\Delta t_i = (t_i - t_{i-1}) \text{ (days)}, \qquad \text{lag}_1 = y_{i-1},$$

$$\begin{aligned}
\bar{y}_{i-}^{(3)} &= \frac{1}{3}\sum_{j=1}^{3} y_{i-j},\\
m_i &= \alpha y_{i-1} + (1-\alpha) m_{i-1},\\
\alpha &= 0.30,\\
m_1 &= y_1.
\end{aligned}$$

where $\bar{y}_{i-}^{(3)}$ is the three-observation rolling mean (shifted so only prior values are used) and m_i is an exponentially weighted moving average of prior chl-a [46]. The feature vector was:

$$x_i = \big[P_i,\, T_i^{\max},\, T_i^{\text{mean}},\, S_{i1},\, C_{i1},\\ \text{month}_i,\, \text{year}_i,\, \Delta t_i,\, y_{i-1},\, m_{i-1},\, \bar{y}_{i-}^{(3)}\big].$$

3.7.2. *Learning Algorithm*

We fit a gradient-boosted decision-tree regressor [47, 48] under squared-error loss. Let $F(x)$ denote the model. With n_{train} training cases and L_2 loss,

$$\min_F L(F) = \sum_{i\in\text{train}} \big(y_i - F(x_i)\big)^2.$$

Boosting constructs an additive model

$$F_M(x) = F_0(x) + \sum_{m=1}^{M} \nu\gamma_m h_m(x; \theta_m),$$

where F_0 is the initial prediction (the training mean under L_2), h_m are regression trees fit to the negative gradients (residuals), γ_m are line-search weights, θ_m are tree parameters, and $\nu \in (0, 1]$ is the learning rate [47]. Predictions are $\hat{y}_i = F_M(x_i)$. This approach lets the model discover thresholds and interactions (e.g., "when it's warm and dry, chlorophyll tends to be higher") without us pre-specifying a formula.

To prevent temporal leakage, we used a chronological split: the earliest 80% of time-ordered observations for training and the most recent 20% for testing [49]. All target-based features (lags, rolling mean, EWMA) were shifted so only information available prior to t_i informed $\hat{y}_i$.

3.7.3. Performance Metrics

We reported mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) on the hold-out set:

$$\mathrm{MAE} = \frac{1}{n_{\mathrm{test}}} \sum_{i \in \mathrm{test}} |y_i - \hat{y}_i|,$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n_{\mathrm{test}}} \sum_{i \in \mathrm{test}} \left(y_i - \hat{y}_i\right)^2}.$$

Analyses were performed in Python using pandas for data handling and the histogram gradient boosting regressor implementation in scikit-learn (`HistGradientBoostingRegressor`). Fourier seasonality and exponentially weighted moving average follow standard time-series foundations [46, 50].

3.8. Welfare Model and Welfare-Loss Estimation

3.8.1. Travel Cost Model Specification

We estimated a single-site travel cost model for recreational angling using a negative binomial count specification with a log-link. We let y_i denote the number of trips taken by angler i. The conditional mean is

$$E[y_i \mid x_i] = \mu_i,$$

$$\log \mu_i = \beta_0 + \beta_c \, \mathrm{travelcost}_i + \beta_q q_i + \varepsilon_i$$

where $\mathrm{travelcost}_i$ is generalized travel cost, q_i is the water-quality index, and ε_i is residual error. Estimation uses clustered (robust) standard errors.

Our objective is valuation of quality-linked welfare—specifically, identifying how changes in perceived water quality (via q) translate into changes in expected trip demand and consumer surplus. Accordingly, we employ a parsimonious specification centered on (i) the travel-cost term that identifies the slope of demand and (ii) the quality index that operationalizes threshold-defined impairment. While demographic covariates (e.g., age, income, education) are sometimes included as demand shifters in travel cost applications to explore heterogeneity or improve fit, their inclusion is not required to recover the welfare measure derived from the travel-cost coefficient in a single-site setting [51]. We treat demographic characteristics as part of unobserved preference heterogeneity captured by ε_i.

Under the log-link/semi-log travel cost model with linear travel cost, the Marshallian consumer surplus (CS) per trip is the reciprocal of the negative travel-cost coefficient:

$$\mathrm{CS}_{\mathrm{trip}} = -\frac{1}{\beta_c}.$$

3.8.2. Aggregation Logic

The final stage of the analysis is to derive the welfare value per trip from the revealed preference travel cost model, translate representative behavioral response to improved water quality into a proportional change in lake-wide angling trips, and value the difference as welfare loss due to chl-*a* exceedances (i.e., the gap between realized welfare under actual quality and the counterfactual welfare if daily chl-*a* did not exceed the threshold t identified in the ordered probit model).

The per-angler welfare under scenario s is

$$W_s^{\mathrm{angler}} = \mathrm{CS}_{\mathrm{trip}} \times \hat{T}_s,$$

and the per-angler welfare change is

$$\Delta W^{\mathrm{angler}} = \mathrm{CS}_{\mathrm{trip}} \left(\hat{T}_{\leq t} - \hat{T}_{\mathrm{actual}}\right).$$

Scaling to lake-level monthly welfare, we make the very conservative assumption that all visitors to the lake are accessing it at Utah Lake State Park (the only access point with a continuous annual visitation estimate). Data on monthly visitation to the lake was obtained from the Utah Division of State Parks [52]. We represent monthly visitation to the lake as V_m and set the share of visitors who fish to 55% following Smith et al. [53].

To reflect the trip response implied by the representative angler, monthly potential angling trips are scaled by the ratio

$$\rho = \frac{\hat{T}_{\leq t}}{\hat{T}_{\mathrm{actual}}},$$

$$A_m^t = \rho \times A_m^{\mathrm{actual}}.$$

Monthly welfare (in dollars) is then computed as

$$W_m^{\mathrm{actual}} = \mathrm{CS}_{\mathrm{trip}} \times A_m^{\mathrm{actual}},$$

$$W_m^t = \mathrm{CS}_{\mathrm{trip}} \times A_m^t,$$

and the monthly welfare loss attributable to quality exceedances is

$$\Delta W_m = W_m^t - W_m^{\mathrm{actual}} = \mathrm{CS}_{\mathrm{trip}} \times A_m^{\mathrm{actual}}(\rho - 1).$$

Annual totals are obtained by summing

$$\sum_{m=1}^{12} \Delta W_m.$$

Table 1
Sociodemographic and Lake Use Characteristics of Utah Lake Anglers ($n = 132$)

Characteristic	n	Mean	Std. Dev.	%
Gender				
Male	104			78.8
Female	28			21.2
Age	131	37.6	13.7	
Education				
Less than high school / Some high school	9			6.9
High school graduate	41			31.3
Vocational certificate / Some college / Associate's degree	40			30.5
Bachelor's degree	32			24.4
Master's degree / Professional degree / Doctoral degree	9			6.9
Income				
Less than \$25,000	18			13.6
\$25,000 to \$34,999	14			10.6
\$35,000 to \$49,999	16			12.1
\$50,000 to \$74,999	33			25.0
\$75,000 to \$99,999	18			13.6
\$100,000 to \$149,999	18			13.6
\$150,000 or more	15			11.3
Lake Use Characteristics				
Trip Frequency *(i.e., trips per year)*	130	26.2	64.0	
Use History *(i.e., years fishing at the lake)*	130	17.1	18.0	
Experience with Water Quality Issues *(i.e., has experienced or is aware of water quality issues at the lake)*				
No	40			30.3
Yes	92			69.7
Travel Cost	132	\$59.03	\$45.01	

4. Results

4.1. Survey Response and Characteristics of Anglers

Between May 26 and August 2, 2022, we conducted 27 site-days of on-site intercept sampling. A total of 384 visitors were approached; 49 individuals (12.8%) declined to participate, 22 (5.7%) were unable to complete the survey due to language barriers, and 45 (11.7%) opted to complete the survey later via email. In total, 290 recreationists completed the survey (268 on-site, 22 via email), yielding a 75.5% response rate. From this full sample, 174 respondents indicated that angling was either their primary reason for visiting Utah Lake on the date they were contacted or one of a set of activities they participated in on that trip to the lake; all subsequent analyses focus exclusively on this angler sub-sample.

Respondent characteristics are summarized in Table 1. Most anglers identified as male (79.8%), and the mean age was 38.5 years. Educational attainment varied, with 30.7% holding at least a bachelor's degree and over 90% reported completion of high school. Household income was similarly mixed; 29.6% of respondents reported annual household incomes exceeding \$100,000, while 35.3% reported incomes below \$50,000.

Angling effort at Utah Lake varied widely. The modal number of fishing trips taken in the previous 12 months was 4, whereas the mean was considerably higher at 22.3 trips, indicating a subset of frequent users who fish at the lake on a very regular (often weekly) basis. Mean years of use was 15.9 (mode = 5), again indicating a core group of long-term users. Awareness and experience with water quality issues were common: 64.8% of anglers reported either direct experience with, or awareness of, water quality problems at Utah Lake (e.g., closures or bloom advisories). Travel costs also varied substantially (mean = \$112.52; mode = \$53.26), reflecting differences in proximity and trip investment.

4.2. Anglers' Aesthetic Thresholds

Table 2 presents the random-effects ordered probit results for anglers' ratings of water suitability for fishing, with predicted probabilities shown in Figure 3. Chl-*a* concentrations were negatively associated with perceived desirability ratings at a marginally significant level ($p = 0.102$), consistent with sensitivity to visible greenness. Turbidity was not a statistically significant predictor ($p = 0.306$), suggesting that anglers may be acclimated to the lake's typically high turbidity or species-specific preferences. Common carp—an abundant and popular target species in Utah Lake—can tolerate highly turbid environments and their feeding behavior is known to exacerbate turbidity [54]. This may normalize anglers to highly turbid conditions.

Behavioral covariates revealed heterogeneity in tolerance. Trip frequency was strongly associated with higher desirability ratings ($p < 0.001$), suggesting acclimatization to variable or degraded water quality, a higher tolerance for risk, or behavioral adaptation such as visiting multiple sites around the lake perceived to have better conditions. It may also indicate that more frequent users have different baseline expectations for water appearance. In contrast, the

Table 2
Results of the Random Effects Ordered Probit Panel Data Models Predicting Anglers' Desirability for Fishing

Independent Variable	Coef.	Robust Std. Err.	z	$P > \|z\|$
Water Quality Indicator				
Chl-a (μg/L)	-0.057	0.035	-1.63	0.102
Turbidity (NTU)	0.003	0.003	1.02	0.306
Respondent Characteristics				
Trip frequency	0.002	0.001	4.34	< 0.001
Use history	0.002	0.003	0.56	0.578
Experience with water quality issues ($0 =$ no, $1 =$ yes)	-0.043	0.094	-0.45	0.650
Gender ($0 =$ male, $1 =$ female)	-0.194	0.131	-1.48	0.138
Photograph Location				
Photograph location ($0 =$ open water, $1 =$ shoreline)	0.003	0.095	0.03	0.977
Travel Cost	-3.89e-04	2.05e-04	-1.90	0.058
Model Characteristics				
Wald $\chi^2(8)$				724.35
Prob $> \chi^2$				< 0.001
σ^2			4.31e-30	(4.18e-27)

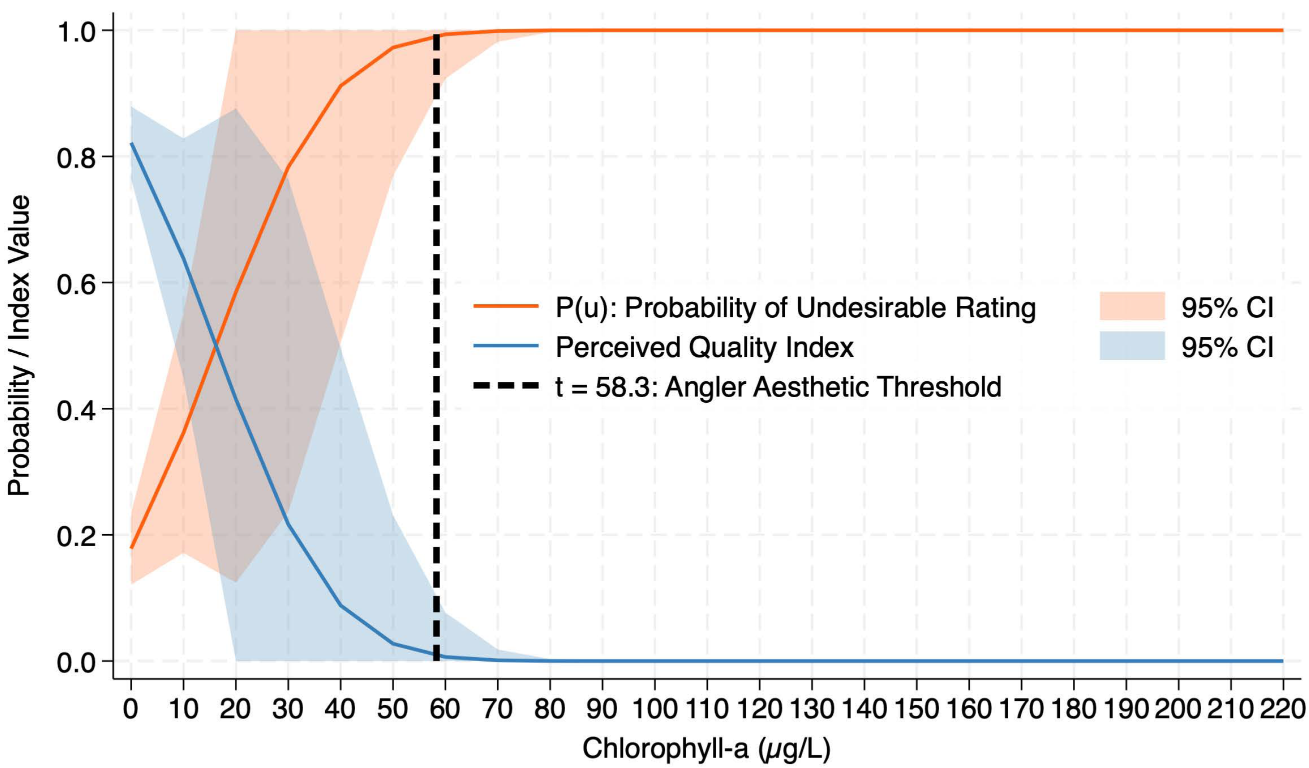

Figure 3: Predicted Probabilities and Perceived Quality Index Derived from the Ordinal Probit Model Estimating Anglers' Aesthetic Preferences.

number of years an angler had been visiting Utah Lake, prior experience/awareness of water quality issues, and gender were not significant predictors of aesthetic preferences ($p =$ 0.578; $p = 0.650$; $p = 0.138$, respectively). Travel cost was marginally associated with lower desirability ($p = 0.058$), suggesting that those investing more in their trips may hold higher expectations for water quality, and thus may be more critical of visible impairments.

To make the threshold behavior explicit, we translate predicted probabilities into the probability that conditions are "undesirable" for angling, defined as the sum of the first three response categories (very/moderately/slightly undesirable). At the oft-cited aesthetic threshold of 20 μg/L chl-*a* [55, 3], the model predicts that approximately 60% of anglers would rate conditions as undesirable for fishing (Figure 3), indicating that a substantial fraction of anglers respond negatively even at relatively modest greenness levels.

Using the probability curve (Figure 3), we define the angler aesthetic threshold, t, as the chl-*a* concentration at which Pr(undesirable) reaches 0.99 (i.e., $q = 0.01$). Under this operational definition, the estimated threshold is $t = 58.3$ μg/L. This angler-derived indicator provides a transparent decision trigger and ensures consistency between the threshold and the perceived quality index q used in the travel cost model (reported below).

4.3. Perceived Quality Index (q) Derived From Angler Thresholds

We converted the ordered-probit predictions into q defined as $q(c) = 1 - \Pr(\text{undesirable} \mid c)$ over a grid of chl-*a* values. For interpretation, q is the predicted probability an angler rates conditions as neutral-or-better (categories 4–7) at a given chl-*a* concentration (Figure 3). In the estimated q curve, perceived quality declines sharply over the range 50–100 μg/L. This mapping is the key linkage between the threshold analysis and the welfare model presented below, enabling daily chl-*a* predictions to be interpreted as a continuous, behaviorally grounded indicator of recreational quality.

4.4. Model Performance for Constructing a Daily chl-*a* Indicator Series

Historical chl-*a* data used to train the histogram-based gradient boosting model spanned over 30 years, dating from July 11, 1989 to July 23, 2019. The dataset of recorded chl-*a* samples exhibits high temporal variability, with some years being sampled heavily and others not at all (Figure 4). Our initial exploration of the historical water quality data revealed that chl-*a* levels are generally low in the winter and spring but exhibit a sharp, volatile rise in the summer. The average concentration peaks in August (∼64 μg/L), aligning with peak summer temperatures. After averaging observations made on the same day, the final dataset contained 109 estimates; equivalent to approximately 3 per year.

As described in Methods, the histogram-based gradient boosting model was trained on the first 80% of the recorded chl-*a* sample with the remaining 20% being held for testing. The model was developed to "fill the gaps" in the sparse dataset and predict daily chl-*a* fluctuations based on local weather (temperature, precipitation) and past water quality states. The model proved to be a very good "historian," as demonstrated by the R^2 value of 0.65 for the training data. It understood the complex relationships in the training data, capturing how heatwaves and previous bloom states drive algae growth. However, the model performed less well with the unseen "future" data (the test data), as evidenced by an R^2 value of 0.25. This gap indicates overfitting—while the model understands the general rules governing chl-*a* concentrations, the specific timing of daily spikes is chaotic and difficult to pinpoint without real-time data inputs. The model captures the seasonality well but misses the specific magnitude of future events.

The feature importance of the model is shown in Table 3. The model relies most heavily on the time gap between samples and on maximum daily temperature, indicating that irregular sampling intervals proxy meaningful exposure dynamics for chl-*a* change and that warm conditions are strongly associated with higher values; by contrast, the first-order persistence term (`Lag1`) and the mean daily temperature add only marginal signal once timing and temperature are included. The cluster of near-zero scores for rolling mean, precipitation, year, month, and exponential weighted moving mean suggests little unique predictive contribution, likely because seasonality is already captured through temperature (especially maximum daily temperature) and timing features. Negative importances for the sine and cosine seasonal terms indicate redundancy or slight overfit—permutation shuffling those variables marginally improves test performance—implying they can be removed without loss. Overall, these results support a streamlined specification centered on days since previous measurement and maximum daily temperature, with limited value from multiple overlapping seasonal encodings or same-day precipitation. Collectively, despite the difficulty in predicting specific daily spikes, the recursive forecast for 2022 provides a valuable baseline for risk management.

Table 3
Feature Importance Derived by the Histogram Gradient Boosting Model

Feature	Importance
Days since previous measurement	0.15
Maximum daily temperature	0.08
Lag1	0.06
Mean daily temperature	0.02
Rolling mean	0.01
Daily precipitation	0.00
Year	0.00
Month	0.00
Exponential Weighted Moving mean	0.00
Day of year (sine)	-0.01
Day of year (cosine)	-0.04

4.5. Daily chl-*a* Estimates for 2022 and Threshold Exceedances

We subsequently applied the histogram gradient boosting model to 2022, the year in which our on-site survey of anglers was conducted. The recursive forecast is shown in Figure 5. The daily forecast (green line) represents the model's daily predictions. It fluctuates significantly because it reacts to daily weather changes (like temperature spikes or rainfall) and the previous day's value. The smooth curve (blue line) fits the daily data to show the underlying seasonal pattern. The horizontal line marks the critical water quality threshold identified via the ordinal probit model above. When the forecast (green/blue lines) crosses above this red line, it suggests nearly all anglers perceive the lake to be "too green" to be desirable for fishing. In 2022, predicted chl-*a* exceeded the threshold of 58.3 μg/L on 83 days, with the longest consecutive exceedance lasting 35 days (between

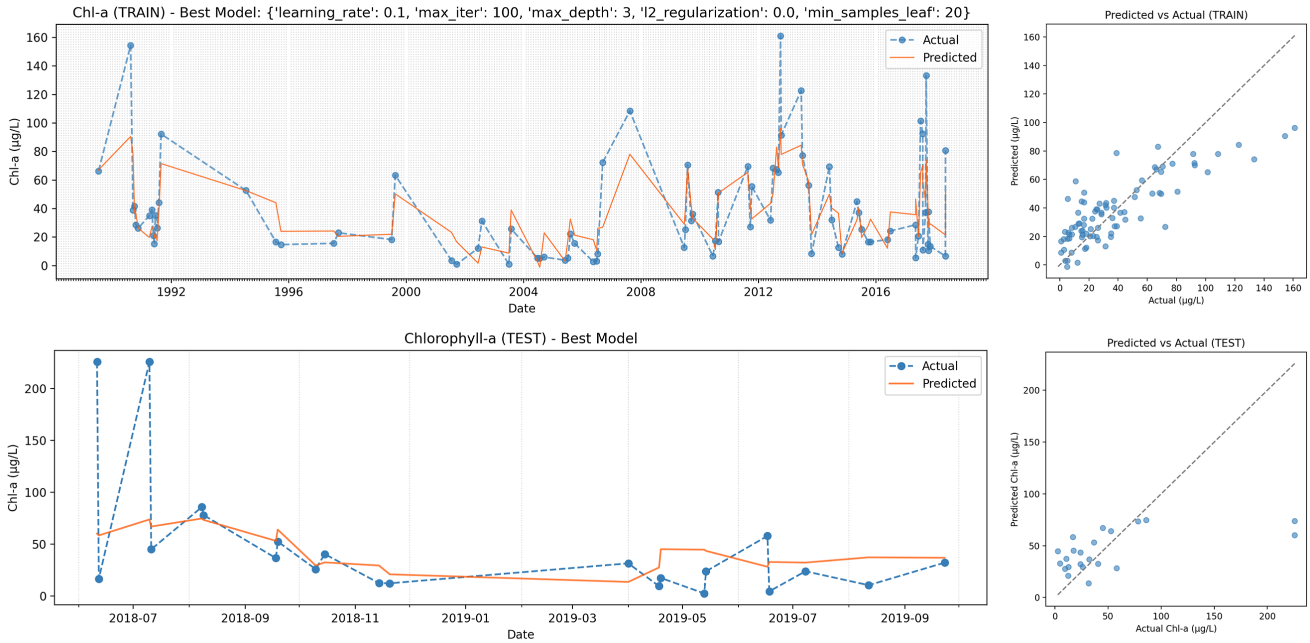

Figure 4: Observed and Predicted chl-*a* Concentrations Derived From the Histogram Gradient Boosting Model (1989-2019).

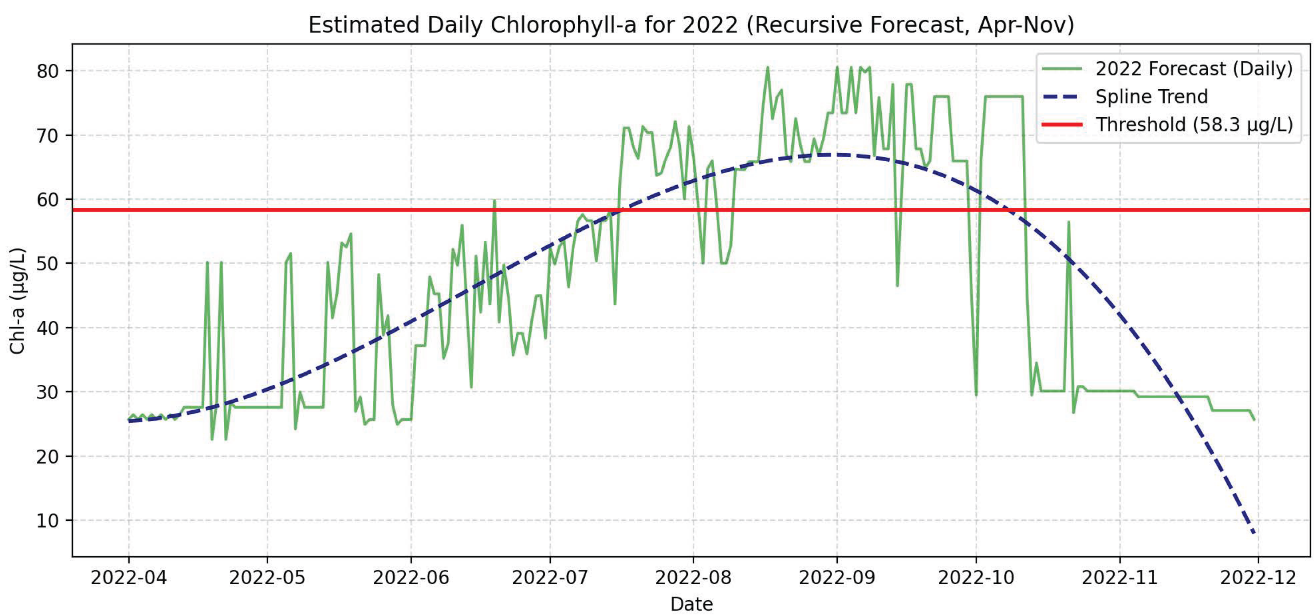

Figure 5: Predicted chl-*a* Concentrations (2022) Derived From the Histogram Gradient Boosting Model.

mid-August and mid-September) and a peak predicted chl-*a* of 80.5 μg/L. Exceedances were concentrated in July (17 days), August (27 days), September (28 days), and October (10 days), aligning with seasonal recreation demand.

4.6. Travel Cost Model, Consumer Surplus, and Welfare-Loss Indicator

The cumulative stage of the analysis involved estimating the travel cost model for Utah Lake anglers, estimating the welfare they derive from fishing at the lake, and applying that welfare estimate to all estimated fishing trips taken to the lake in 2022. Finally, the last step involved estimating the difference in the predicted number of fishing trips taken to the lake in 2022 under predicted chl-*a* concentrations (and the mean welfare derived from recreational angling at the lake) and comparing predicted trips (and welfare) to a scenario in which chl-*a* concentrations never exceed the aesthetic threshold of 58.3 μg/L.

Table 4
Results of the Negative Binomial Log-Link Travel Cost Model ($n = 130$)

Independent Variable	Coef.	Robust Std. Err.	z	$P > \|z\|$
Travel cost	-0.012	0.003	-4.55	< 0.001
Perceived Quality Index	4.199	1.589	2.64	0.008
Constant	4.255	0.310	13.72	< 0.001
Model Characteristics				
Wald $\chi^2(2)$				42.7
Prob > χ^2				< 0.001
Pseudo R^2				0.025

In the negative binomial log-link travel cost model (Table 4), the travel cost coefficient is negative and highly significant ($\beta = -0.012$, SE = 0.003, $z = -4.55$, $p < 0.001$), indicating a downward-sloping demand: each additional dollar of generalized cost reduces the expected trip rate by about 1.2% (exp[-0.012] $\approx$ 0.988). The perceived quality index coefficient is also highly significant and positive ($\beta = 4.199$, SE = 1.589, $z = 2.64$, $p = 0.008$), implying that as perceived water quality increases, expected trips rise. Using the semi-log travel cost model result, the implied Marshallian consumer surplus per trip is approximately \$85.42 with a 95% interval of \$48.63–\$122.21. Overall model fit is typical for single-site count travel cost models (Wald $\chi^2(2) = 42.7$, $p < 0.001$; pseudo $R^2 = 0.025$) and supports the use of the estimated cost coefficient for welfare calculations and of the quality index as a behaviorally meaningful predictor of angling trips.

Table 4 translates these estimates into per-angler and aggregate welfare outcomes for 2022. For clarity, the counterfactual does not assume that anglers "fish more than is feasible," nor does it impose a specific behavioral rule on any individual respondent. Instead, it replaces the observed daily water-quality path in 2022 with a quality-improved scenario in which daily chl-*a* is capped at the aesthetic threshold (58.3 μg/L), and then uses the estimated demand function to compute the resulting expected trip rate holding travel costs and other model inputs constant. In other words, the counterfactual is best interpreted as the number of trips that would be expected, on average, if bloom-driven visual impairment were absent (as defined by the threshold), not as a prediction that any particular angler must exceed their own historical maximum.

Under observed 2022 conditions, the representative angler is predicted to take 21.21 trips; under the no-exceedance counterfactual, the predicted expected number of trips increases to 33.84 ($\Delta = +12.63$ trips), implying an increase in annual consumer surplus from approximately \$1,800 to \$2,900 per angler. Aggregated to the lake level using monthly visitation scaling, total angling trips increase from 118,627 to 189,244 (+59.5%), and total consumer surplus increases from \$10.1 million to \$16.2 million. The implied annual welfare loss attributable to chl-*a* exceedances above the threshold is therefore \$6.0 million (2022 USD), defined as the difference between counterfactual and observed welfare totals.

The month-by-month counterfactual differences should be interpreted similarly. Because the model produces population-level expected trips (not bounded by the maximum trip count observed in the sample under impaired conditions), monthly counterfactual increases can exceed the maximum observed trips in the data without implying logistically impossible behavior. Accordingly, the counterfactual should be viewed as an estimate of the incremental trips and welfare attributable to removing threshold-defined impairment, rather than a literal forecast of realized trips for each angler in each month.

Monthly welfare impacts nevertheless mirror visitation intensity and the seasonal timing of exceedances. The largest absolute welfare differences occur in high-use months; for example, both August and September increase by approximately 23,000 trips and \$2.0 million in surplus under the no-exceedance scenario (Figure 6). To make the welfare-loss indicator operational for management, Table 5 reports monthly observed welfare, counterfactual welfare, and welfare loss, along with monthly exceedance days.

5. Discussion

This study asked whether a routinely monitored biophysical indicator of bloom conditions (chl-*a*) can be translated—despite sporadic measurement frequency—into decision-relevant, human-use outcomes for a recreational fishery. The study also asked whether the exceedance of a user-defined aesthetic threshold produces meaningful welfare losses. The answer is yes. Anglers exhibited a clear threshold response to increasing "greenness" where the perceived suitability for fishing deteriorated sharply. In addition, chl-*a* concentrations surpassed the angler-defined threshold frequently during the peak recreation season, which translates into large, policy-relevant welfare losses. The integrated workflow—threshold elicitation, construction of a daily indicator series, translation of that series into a behaviorally grounded quality index, and valuation through a travel cost model—demonstrates how conventional water-quality monitoring can be extended into an outcome-oriented indicator framework that is directly interpretable for management.

Beyond simply confirming that anglers respond to visible bloom conditions, the results show that (i) perceptions

Table 5

Differences in Trips and Consumer Surplus for a Typical Utah Lake Angler and All Anglers to the Lake in 2022 Under Predicted Daily Chl-a Concentrations (baseline scenario) and a Scenario in Which Daily Chl-*a* Concentrations Never Exceed Anglers' Aesthetic Threshold of 58.3 μg/L (No Impairment Scenario)

	Baseline Scenario: Predicted Daily Chl-a Concentrations			**No Impairment Scenario**	
Estimate	**Trips**	**Consumer Surplus** (2022 millions $USD)	**Exceedance Days**	**Trips**	**Consumer Surplus** (2022 millions $USD)
Typical Angler					
Annual Estimates	21.21	1.8		33.84	2.9
All Lake Anglers					
January	2,186	0.19	0	2,186	0.19
February	2,456	0.21	0	2,456	0.21
March	4,263	0.36	0	4,263	0.36
April	9,440	0.81	0	9,440	0.81
May	16,443	1.40	0	16,443	1.40
June	32,451	2.77	1	33,301	2.84
July	18,828	1.61	17	33,291	2.84
August	12,497	1.07	27	35,468	3.03
September	8,925	0.76	28	32,747	2.80
October	6,280	0.54	10	14,788	1.26
November	1,374	0.12	0	1,374	0.12
December	3,485	0.30	0	3,485	0.30
Annual Estimates	118,627	10.13	85	189,244	16.16

are nonlinear and can be operationalized as an explicit trigger, (ii) sparse monitoring can be "densified" into a daily indicator series that is usable for linking environmental conditions to behavior, and (iii) those linkages matter economically at the scale relevant to lake governance. In practical terms, the study converts an ecologically meaningful proxy (chl-*a*) into an outcome indicator grounded in stakeholder preferences and expressed as recreational welfare—an outcome that is directly legible to decision-makers tasked with prioritizing nutrient reduction, communicating risk, and justifying investments in environmental restoration.

5.1. Contributions to the Literature

5.1.1. Nonlinear Perceptions and the Role of Aesthetic Thresholds

The threshold behavior documented here aligns with a broader body of research showing that recreationists' evaluations of water quality are often discontinuous rather than smooth: people tolerate incremental changes up to a point, but once visible cues cross an acceptability boundary, ratings and intended use can change quickly. This has been shown across systems and activities where "optical water quality" (clarity, color, surface scums) drives immediate judgments of suitability and risk. Angradi and colleagues [5] synthesize evidence that recreational benefits are closely tied to clarity-related and appearance-related indicators, with threshold-like patterns in perceived suitability. West and colleagues [6, 7] similarly demonstrate that optical cues structure perceived suitability in rivers, reinforcing that perceptual judgments are anchored in what users can see, not solely in measured chemistry.

In Utah Lake, this nonlinear pattern was operationalized by defining anglers' aesthetic threshold as the chl-*a* level at which the probability of an "undesirable" rating becomes nearly certain; under that definition, the threshold estimate implies that managers can meaningfully interpret the indicator not only as "higher is worse," but as "above this point, the fishery is functionally impaired for nearly all anglers." Importantly, the study also demonstrates that the mapping from chl-*a* to perceived quality is steepest in a management-relevant band (under 50 μg/L), suggesting that relatively modest changes in bloom intensity within that range can generate disproportionately large shifts in user experience and behavior.

5.1.2. The Uniqueness of Optically Complex Lakes

A key contextual point is that Utah Lake is not a clear water system; wind-driven resuspension and high background turbidity can influence what "green" looks like, how confidently anglers attribute greenness to algae, and how they interpret risk. In the broader literature, thresholds for perceived impairment vary substantially across systems, and optical complexity is a plausible driver of that heterogeneity. In clear lakes, relatively modest chl-*a* can be visually salient and quickly interpreted as degradation; but in turbid systems, users may either normalize poorer appearance or require more intense bloom conditions before judging the lake "too green." This general pattern is consistent with the cross-system evidence summarized by Angradi et al. [5] regarding how biophysical indicators translate into recreation-related perceptions.

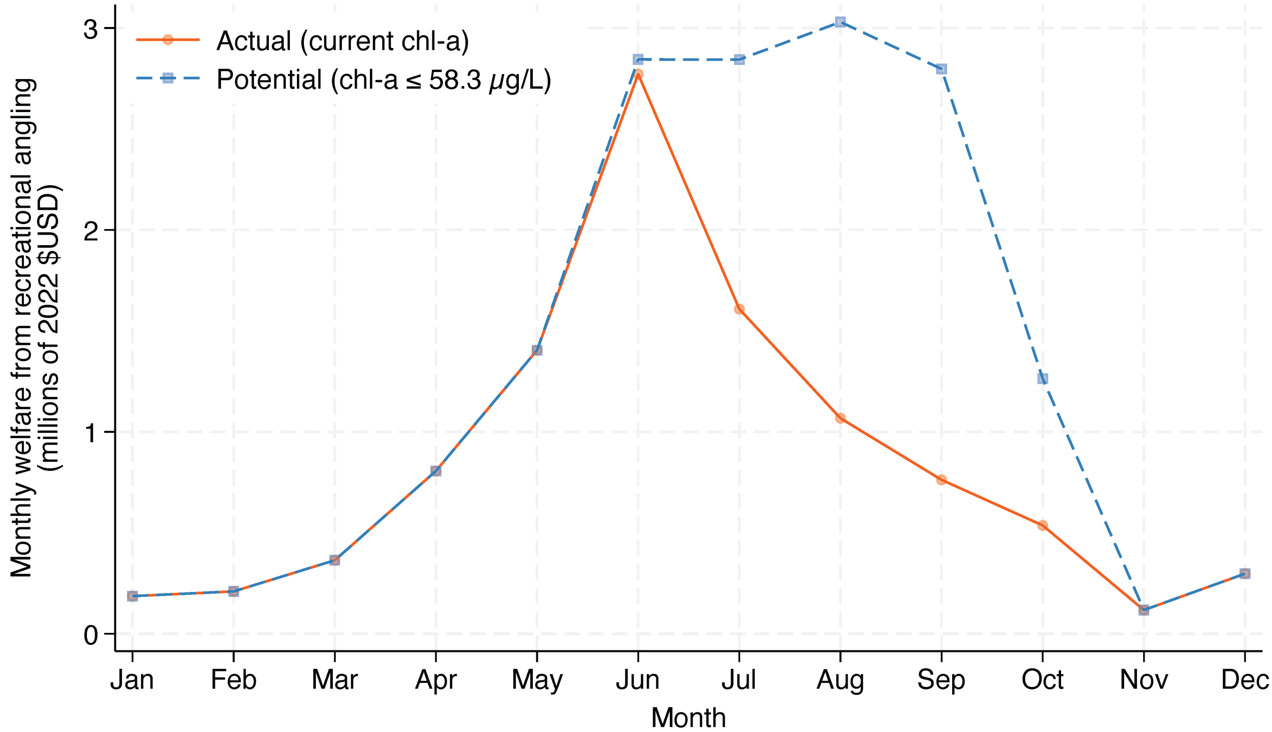

Figure 6: Predicted Angling Trips to Utah Lake Under the Baseline Scenario (*chl-a* Follows Historical Trends) and a No Impairment Scenario (*chl-a* Never Exceeds 58.3 μg/L).

The present findings also suggest that turbidity, at least within the range represented in the photo set, was not the primary driver of suitability judgments in the angling context, while trip frequency was associated with greater tolerance. One interpretation is habituation: frequent users recalibrate expectations, learn where and when conditions are acceptable, or maintain participation because angling motivations (tradition, convenience, target species) partially offset aesthetic conditions and concerns. Another interpretation is that anglers' preferences reflect activity-specific tradeoffs. In some systems, productive (eutrophic) conditions may be perceived as compatible with fish abundance (up to a point); once blooms are sufficiently intense to trigger strong visual aversion or health concerns, the disutility dominates. The observed steep decline in perceived quality under 100 μg/L is consistent with that "tipping" dynamic.

5.1.3. Advancing From Sporadic Monitoring to a Daily Indicator Series

A second contribution concerns the indicator gap created by sporadic sampling: management decisions (communication, advisories, resource allocation) often operate on daily-to-weekly timescales, while chl-*a* measurements may occur only a few times per year. The study responds to this gap by using a histogram-based gradient boosting model to translate a sparse historical record into a daily indicator series. The model captured broad seasonal structure well in training but generalized more weakly to held-out observations, which we interpret as a predictable limitation when forecasting sudden events from limited in situ data.

This pattern is broadly consistent with water-quality forecasting research showing that tree-based ensemble methods can be strong "historians" and useful interpolators, even when predicting exact day-to-day spikes remains difficult without dense monitoring or real-time drivers. Savoy and Harvey [25], for example, use extreme gradient boosting to predict daily chlorophyll dynamics at scale, illustrating both the promise of these methods and the importance of data richness and driver representation. From an ecological-indicator perspective, the key point is not perfect daily prediction but the production of a temporally continuous decision support series that can be linked consistently to use outcomes and evaluated against thresholds.

5.1.4. Translating a Biophysical Indicator Into an Outcome Indicator: Welfare Impacts

The methodological workflow demonstrated here linked chl-*a* (biophysical indicator) to a perceived quality index (socially grounded indicator) to angling trips (behavior) to consumer surplus (welfare). The perceived quality index is explicitly defined as the probability that anglers rate conditions neutral-or-better, making it an interpretable, continuous outcome-relevant indicator in its own right. When embedded in the travel cost model, higher perceived quality was associated with higher trip rates, consistent with the recreation demand literature that treats site quality as a determinant of use and value. This approach is complementary to prior harmful algal bloom valuation work that infers behavioral response from permits or visitation patterns. For example, Wolf and colleagues [34] estimate recreational damages associated with harmful algal bloom variation in Lake Erie using fishing permit sales, demonstrating that bloom conditions can measurably depress participation.

Critically, the welfare-loss estimates produced here are not merely academic; they sit within the same order of magnitude as widely cited assessments of eutrophication's recreational damages and harmful algal bloom-related economic impacts. Dodds et al. [32] estimate that eutrophication imposes substantial annual economic damages in U.S. freshwaters, with recreation comprising a major component of those losses. The U.S. National Office of Harmful Algal Blooms [2] similarly reports that harmful algal blooms generate meaningful economic impacts, with average annual losses in the tens of millions of dollars and single events producing large localized shocks. This study contributes to this literature by clarifying how a familiar monitoring metric can be operationalized into a welfare-based outcome indicator using an explicit, stakeholder-defined threshold and a reproducible workflow.

5.2. Implications for Indicator Science and Management Practice

5.2.1. Implications for Indicator Use

The paper's core implication is that chl-*a* can function not only as a proxy for bloom biomass, but as a decision trigger and an input into a suite of outcome indicators when it is (i) calibrated to user perceptions and (ii) temporally aligned with decision cycles. The angler-defined threshold provides a transparent criterion for impairment that is grounded in stakeholder judgments rather than purely limnological convention. The perceived quality index extends this by converting chl-*a* into a continuous probability measure of acceptability that is directly compatible with economic and behavioral modeling. Together, these steps represent a generalizable template for transforming ecological monitoring data into policy-relevant indicators that integrate social valuation.

This work also aligns with Environmental Protection Agency [38] guidance emphasizing that user perception surveys can support development of criteria and translators that connect nutrient pollution to designated uses. In practice, it provides agencies with a defensible approach for bridging the persistent communication gap between "the lake is at X μg/L" and "what does that mean for the public and for management decisions?"

5.2.2. Implications for Management and Communication

From a management standpoint, the results support two applied takeaways. First, communication can be threshold-based and grounded in users' perceptions. Rather than reporting chl-*a* as an abstract concentration, managers can describe conditions relative to an angler-defined impairment threshold and expected user response (e.g., "above this level, most anglers view conditions as unacceptable"). This reduces ambiguity and increases the relevance of monitoring updates. Second, welfare-based outcome indicators support prioritization and appraisal. The annual and monthly welfare-loss indicators translate water-quality impairment into a metric that can be directly compared to program costs, restoration investments, or alternative interventions. The welfare-loss estimate on the order of several million dollars provides a policy-relevant magnitude that can inform cost-effectiveness discussions and funding justification, especially when paired with uncertainty bounds and sensitivity analyses. These implications strengthen the argument that indicator systems should be designed not only to detect ecological change, but to enable decisions: defining triggers, quantifying consequences, and communicating meaning to stakeholders.

5.3. Limitations

Several limitations warrant transparent discussion, primarily around (i) measurement and representation, (ii) model structure and uncertainty, and (iii) aggregation assumptions.

First, the perceptual threshold is derived from a photo-elicitation approach using a curated set of images paired with in situ measurements. While this design is useful for isolating visual cues, photographs cannot fully reproduce sensory experience (odor, scums moving with wind, social context), and the image set necessarily samples a finite range of conditions. The operational threshold definition is transparent and internally consistent with the quality index, but alternative definitions (e.g., 50% undesirability or thresholds tailored to different decision contexts) could yield different numeric trigger levels. These limitations suggest that the threshold should be interpreted as a defensible, stakeholder-grounded decision aid rather than a universal "truth," and motivate future work on segmented thresholds and alternative impairment definitions.

Second, the machine learning model's weaker generalization to held-out data indicates uncertainty in the precise day-to-day reconstruction of chl-*a* peaks. This limitation is expected under sparse, irregular historical sampling and a limited set of predictors. Importantly, the principal purpose here is to generate a continuous daily indicator series that can be linked to outcomes. Imperfect daily precision does not negate the core inference that exceedances cluster during peak use periods and are associated with meaningful welfare losses. Nonetheless, it motivates data enrichment (e.g., remote sensing, continuous sensors) and uncertainty propagation as future improvements.

Third, the recreation demand model is a single-site travel cost framework. As with many single-site models, it does not explicitly represent substitution across alternative fisheries, nor does it incorporate an explicit participation constraint (an "outside option") that may be particularly relevant during the late-summer and holiday months when recreation time budgets shift and high-quality conditions may not translate into proportional increases in fishing trips. This limitation can affect the magnitude and seasonal distribution of counterfactual trip changes, though it is less likely to overturn the primary conclusion that bloom-driven quality impairment reduces welfare. It also provides a clear rationale for future site choice models with outside options and for integrating contingent behavior questions to better capture quality-driven participation changes.

Finally, the lake-level scaling relies on visitation assumptions and a fishing-share parameter. These assumptions affect absolute magnitudes, but they do not negate the central conclusion that threshold exceedances coincide with peak-use periods and imply meaningful welfare consequences. The direction and management relevance of the results are robust to reasonable variation in scaling parameters; future work can tighten these estimates with richer survey and indicator data.

5.4. Future Directions

The workflow developed here is intentionally replicable, and several concrete extensions would materially strengthen both indicator science and management applicability. These include:

- Integrate remote sensing and real-time sensors to improve daily series fidelity. The predictive limitations noted for the histogram gradient boosting model point directly to data enrichment. Pairing in situ chl-*a* with satellite-derived reflectance products and/or continuous in-lake measurements can improve event timing, reduce overfitting risk, and better resolve short-lived bloom events. A practical next step is an operational "nowcast" that updates daily estimates and exceedance probabilities as new observations become available.

- Move from single-site demand to site-choice/ substitution models with an explicit outside option. To better capture behavioral adaptation, a multi-site model (e.g., random utility/site choice or repeated-choice travel cost) could quantify how anglers substitute across regional fisheries in response to bloom conditions. Importantly, such models should also include an outside option (no fishing trip/alternative activity) to reflect seasonal participation constraints and shifting recreation portfolios, particularly during late-summer and holiday months when high-quality conditions may not translate into proportional increases in fishing effort. This extension would yield welfare measures more consistent with modern recreation demand modeling and would help managers distinguish welfare losses due to displacement (site switching) from welfare losses due to foregone participation.

- Incorporate contingent behavior to strengthen inference on quality-driven participation changes. A follow-up travel cost study could include contingent behavior questions that elicit intended trip adjustments under clearly defined water-quality scenarios (e.g., chl-*a* below/above the threshold; presence/absence of visible scums; alternative advisory language; and, where feasible, toxin-risk framing). These data can be integrated into the recreation demand system to estimate quality-induced trip changes more directly, validate the revealed preference quality index, and improve inference in months when participation is plausibly constrained by travel, work schedules, or substitution to other activities.

- Link threshold exceedances to observed participation signals. The study demonstrates the conceptual linkage between exceedance days and welfare. A next step is empirical validation using independent participation proxies—mobile-device visitation patterns at access points, boat ramp counts, or creel survey effort—similar to prior harmful algal bloom participation studies. This would strengthen causal inference and provide an additional outcome indicator ("effort lost") that complements welfare.

- Expand from "aesthetic impairment" to "risk-based impairment" using toxin metrics. Because chl-*a* is an imperfect proxy for toxicity, a meaningful extension would integrate microcystin (or other toxin) monitoring and model dual-threshold conditions: one threshold for aesthetic impairment (use deterrence) and another for health-risk advisories. This would more directly support advisory design and risk communication, while maintaining the stakeholder-centered indicator approach.

- Segment-specific thresholds and equity-relevant indicators. The finding that frequent users exhibit higher tolerance to degraded water conditions suggests heterogeneous thresholds across user groups. Future analyses could estimate latent classes (e.g., high-frequency local anglers vs. occasional visitors) and produce segmented thresholds and welfare impacts. For management, this would support more targeted messaging and improve understanding of who bears the welfare burden of blooms.

Taken together, these steps can advance the workflow toward an operational indicator system capable of supporting adaptive management, public communication, and economic appraisal at the temporal scale where bloom decisions are made.

6. Conclusion

This study demonstrates how a routinely monitored biophysical variable—chl-*a*—can be transformed from an intermittently measured proxy of bloom conditions into a coherent, management-facing indicator system that is directly interpretable in terms of recreational outcomes. By coupling angler photo-elicitation with indicator modeling and economic valuation, the work shows that the consequences of bloom dynamics are not simply "more or less" degradation; rather, anglers exhibit nonlinear responses that concentrate behavioral and welfare impacts around a stakeholder-defined aesthetic threshold. When this threshold is embedded within a perceived quality index and paired with a daily chl-*a* series, the resulting indicator suite links ecological variability to recreation demand at the temporal scale where management decisions and public communication actually occur. In combination, these elements resolve a common disconnect in eutrophication and HAB governance: managers may know that bloom indicators are worsening, but lack an empirically grounded way to interpret what those changes mean for human use and welfare.

The primary contribution to the field is methodological and conceptual. Methodologically, the study offers a replicable workflow that integrates threshold elicitation, machine-learning-based temporal refinement of indicators, index construction, and welfare-based outcome quantification. Conceptually, it advances indicator science by demonstrating how stakeholder-defined thresholds can serve as the bridge between ecological monitoring and valuation—moving beyond descriptive reporting of water quality toward politically relevant, scientifically rigorous assessment of use impairment. This approach is broadly transferable to bloom-prone aquatic systems where monitoring is sparse, recreational values are high, and management requires clear triggers and defensible metrics for prioritizing interventions. Collectively, this indicator-based approach helps managers translate water quality into clear, actionable measures of recreational impact.

CRediT authorship contribution statement

Jordan W. Smith: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Supervision; Visualization; Writing – original draft.. **Chase C. Lamborn:** Data curation; Investigation; Supervision; Writing – review & editing..

References

[1] L. Feng, Y. Wang, X. Hou, B. Qin, T. Kutser, F. Qu, N. Chen, H. W. Paerl, C. Zheng, Harmful algal blooms in inland waters. Nature Reviews Earth & Environment 5 (2024) . https://doi.org/10.1038/s43017-024-00578-2.

[2] U.S. National Office of Harmful Algal Blooms, Harmful algal research & response: A national environmental science strategy (HARRNESS), 2024-2034, Technical Report, Woods Hole Oceanographic Institution, Woods Hole, MA. 2024. https://doi.org/10.1575/1912/69773.

[3] M. V. Hoyer, C. D. Brown, D. E. Canfield, Relations between water chemistry and water quality as defined by lake users in Florida. Lake and Reservoir Management 20 (2004) . https://doi.org/10.1080/07438140409354247.

[4] U. Schirpke, R. Scolozzi, U. Tappeiner, "A Gem among the Rocks"—Identifying and Measuring Visual Preferences for Mountain Lakes. Water 13 (2021) . https://doi.org/10.3390/w13091151.

[5] T. R. Angradi, P. L. Ringold, K. Hall, Water clarity measures as indicators of recreational benefits provided by U.S. lakes: Swimming and aesthetics. Ecological Indicators 93 (2018) . https://doi.org/10.1016/j.ecolind.2018.06.001.

[6] A. O. West, J. M. Nolan, J. T. Scott, Optical water quality and human perceptions: a synthesis. WIREs Water 3 (2016) . https://doi.org/10.1002/wat2.1127.

[7] A. O. West, J. M. Nolan, J. T. Scott, Optical water quality and human perceptions of rivers: an ethnohydrology study. Ecosystem Health and Sustainability 2 (2016) . https://doi.org/10.1002/ehs2.1230.

[8] J. C. Nabout, A. C. M. David, J. F. Felipe, K. B. Machado, L. Carvalho, H. F. d. Cunha, Can people detect the loss of water quality? A field experiment to evaluate the correlation between visual perception and water eutrophication degree. Acta Limnologica Brasiliensia 34 (2022) . https://doi.org/10.1590/S2179-975X2921.

[9] A. J. Smith, B. T. Duffy, M. A. Novak, Observer rating of recreational use in wadeable streams of New York State, USA: Implications for nutrient criteria development. Water Research 69 (2015) . https://doi.org/10.1016/j.watres.2014.11.022.

[10] J. W. Smith, Public awareness and visual water quality thresholds at a bloom-prone urban lake (Utah Lake, Utah, USA). Lake and Reservoir Management 42 (2026) . https://doi.org/10.1080/10402381.2025.2578752.

[11] D. Gill, M. Rowe, S. J. Joshi, Fishing in greener waters: Understanding the impact of harmful algal blooms on Lake Erie anglers and the potential for adoption of a forecast model. Journal of Environmental Management 227 (2018) . https://doi.org/10.1016/j.jenvman.2018.08.074.

[12] D. H. Jayasekera, R. T. Melstrom, K. L. Pope, Economic losses to inland recreational fisheries from harmful algal blooms. Journal of Environmental Management 372 (2024) . https://doi.org/10.1016/j.jenvman.2024.123238.

[13] D. Wolf, W. Chen, S. Gopalakrishnan, T. C. Haab, H. A. Klaiber, The impacts of harmful algal blooms and E. coli on recreational behavior in Lake Erie. Land Economics 95 (2019) . https://doi.org/10.3368/le.95.4.455.

[14] D. N. Khoi, N. T. Quan, D. Q. Linh, P. T. T. Nhi, N. T. D. Thuy, D. N. Khoi, N. T. Quan, D. Q. Linh, P. T. T. Nhi, N. T. D. Thuy, Using machine learning models for predicting the water quality index in the La Buong River, Vietnam. Water 14 (2022). https://doi.org/10.3390/w14101552.

[15] K. Merabet, F. Di Nunno, F. Granata, S. Kim, R. M. Adnan, S. Heddam, O. Kisi, M. Zounemat-Kermani, Predicting water quality variables using gradient boosting machine: global versus local explainability using SHapley Additive Explanations (SHAP). Earth Science Informatics 18 (2025) . https://doi.org/10.1007/s12145-025-01796-y.

[16] F. U. Shah, A. U. Khan, A. W. Khan, B. Ullah, M. R. Khan, I. Javed, Comparative analysis of ensemble learning algorithms in water quality prediction. Journal of Hydroinformatics 26 (2024) . https://doi.org/10.2166/hydro.2024.071.

[17] E. Smeltzer, S. A. Heiskary, Analysis and applications of lake user survey data. Lake and Reservoir Management 6 (1990) . https://doi.org/10.1080/07438149009354701.

[18] G. Scheufele, S. Pascoe, Ecosystem accounting: Reconciling consumer surplus and exchange values for free-access recreation. Ecological Economics 212 (2023) . https://doi.org/10.1016/j.ecolecon.2023.107905.

[19] R. J. Johnston, M. H. Ranson, E. Y. Besedin, E. C. Helm, What determines willingness to pay per fish? A meta-analysis of recreational fishing values. Marine Resource Economics 21 (2006) . https://doi.org/10.1086/mre.21.1.42629492.

[20] I.-M. Gren, G. Marbuah, Willingness to pay for recreational fisheries in Europe. Fisheries Management and Ecology 31 (2024) . https://doi.org/10.1111/fme.12719.

[21] J. C. Whitehead, L. Cornicelli, L. Bragg, R. Southwick, The aggregate economic value of Great Lakes recreational fishing trips. Journal of Great Lakes Research 51 (2025) . https://doi.org/10.1016/j.jglr.2025.102529.

[22] S. Pouso, S. Ferrini, R. K. Turner, Borja, M. C. Uyarra, Monetary valuation of recreational fishing in a restored estuary and implications for future management measures. ICES Journal of Marine Science 77 (2020) . https://doi.org/10.1093/icesjms/fsz091.

[23] G. Grilli, G. Landgraf, J. Curtis, S. Hynes, A travel cost evaluation of the benefits of two destination salmon rivers in Ireland. Journal of Outdoor Recreation and Tourism 23 (2018) . https://doi.org/10.1016/j.jort.2018.02.004.

[24] K. J. Egan, J. A. Herriges, C. L. Kling, J. A. Downing, Recreation demand using physical measures of water quality, Working Paper 18496, Hebrew University of Jerusalem Archive, Center for Agricultural and Rural Development. 2004. https://ideas.repec.org//p/ags/hebarc/18496.html.

[25] P. Savoy, J. W. Harvey, Predicting daily river chlorophyll concentrations at a continental scale. Water Resources Research 59 (2023) . https://doi.org/10.1029/2022WR034215.

[26] J. Park, K. Patel, W. H. Lee, Recent advances in algal bloom detection and prediction technology using machine learning. Science of The Total Environment 938 (2024) . https://doi.org/10.1016/j.scitotenv.2024.173546.

[27] C. Ma, J. Zhao, G. Zhang, Decoding the drivers of variability in chlorophyll-a concentrations in the Pearl River Estuary: Intra-annual and inter-annual analyses of environmental influences. Environmental Research 268 (2025) . https://doi.org/10.1016/j.envres.2025.120783.

[28] S. Lin, D. C. Pierson, J. P. Mesman, Prediction of algal blooms via data-driven machine learning models: an evaluation using data from a well-monitored mesotrophic lake. Geoscientific Model Development 16 (2023) . https://doi.org/10.5194/gmd-16-35-2023.

[29] W. K. Dodds, W. W. Bouska, J. L. Eitzmann, T. J. Pilger, K. L. Pitts, A. J. Riley, J. T. Schloesser, D. J. Thornbrugh, Eutrophication of U.S. Freshwaters: Analysis of Potential Economic Damages. Environmental Science & Technology 43 (2009) . https://doi.org/10.1021/es801217q.

[30] J. N. Pretty, C. F. Mason, D. B. Nedwell, R. E. Hine, S. Leaf, R. Dils, Environmental costs of freshwater eutrophication in England and Wales. Environmental Science & Technology 37 (2003) . https://doi.org/10.1021/es020793k.

[31] V. H. Smith, S. B. Joye, R. W. Howarth, Eutrophication of freshwater and marine ecosystems. Limnology and Oceanography 51 (2006) . https://doi.org/10.4319/lo.2006.51.1_part_2.0351.

[32] L. C. Backer, Impacts of Florida red tides on coastal communities. Harmful Algae 8 (2009) . https://doi.org/10.1016/j.hal.2008.11.008.

[33] D. Wolf, W. Georgic, H. A. Klaiber, Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry. Journal of Environmental Management 199 (2017) . https://doi.org/10.1016/j.jenvman.2017.05.031.

[34] D. Wolf, H. A. Klaiber, Bloom and bust: Toxic algae's impact on nearby property values. Ecological

Economics 135 (2017) . https://doi.org/10.1016/j.ecolecon.2016.12.007.

[35] S. Braegger. Understanding water levels at Utah Lake, https://utahlake.gov/understanding-water-levels-at-utah-lake/, 2016.

[36] June Sucker Recovery Implementation Program. Utah Lake: Facts & History, https://www.junesuckerrecovery.org/resources-outreach/utah-lake-facts-history, 2025.

[37] S. A. Miller, T. A. Crowl, Effects of common carp (Cyprinus carpio) on macrophytes and invertebrate communities in a shallow lake. Freshwater Biology 51 (2006) . https://doi.org/10.1111/j.1365-2427.2005.01477.x.

[38] Environmental Protection Agency, Development of user perception surveys to protect water quality from nutrient pollution: A primer on common practices and insights, Technical Report EPA 823-R-21-001, U.S. Environmental Protection Agency, Washington, D.C.. 2021. https://www.epa.gov/sites/default/files/2021-04/documents/development-user-perception-surveys-4-2021.pdf.

[39] P. Jakus, M., N. Nelson, J. Ostermiller, Using survey data to determine a numeric criterion for nutrient pollution. Water Resources Research 53 (2017) . https://doi.org/10.1002/2017WR021527.

[40] A. M. Votruba, J. R. Corman, Definitions of water quality: A survey of lake-users of water quality-compromised lakes. Water 12 (2020) . https://doi.org/10.3390/w12082114.

[41] D. J. Phaneuf, V. K. Smith, Recreation demand models, in: K. G. Mäler, J. Vincent (Eds.), Handbook of environmental economics, Elsevier, 2005.

[42] K. K. Pflugh, L. Lurig, L. A. Von Hagen, S. Von Hagen, J. Burger, Urban anglers' perception of risk from contaminated fish. Science of The Total Environment 228 (1999) . https://doi.org/10.1016/S0048-9697(99)00048-0.

[43] StataCorp, LLC, Stata: Release 18. Statistical software., StataCorp LP, College Station, TX. 2023.

[44] Utah Divison of Water Quality. Utah Lake data explorer, https://udwq.shinyapps.io/UtahLakeDataExplorer/, 2025.

[45] Meteostat. The Weather's Record Keeper, https://meteostat.net/en/, 2025.

[46] Linear innovations state space models with random seed states, in: R. Hyndman, A. Koehler, K. Ord, R. Snyder (Eds.), Forecasting with Exponential Smoothing: The State Space Approach, Springer, Berlin, Heidelberg, 2008. pp. . https://doi.org/10.1007/978-3-540-71918-2_12.

[47] J. H. Friedman, Greedy function approximation: A gradient boosting machine. The Annals of Statistics 29 (2001) . https://www.jstor.org/stable/2699986.

[48] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, Duchesnay, Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12 (2011). https://www.jmlr.org/papers/volume12/pedregosa11a/pedregosa11a.pdf.

[49] C. Bergmeir, J. M. Benítez, On the use of cross-validation for time series predictor evaluation. Information Sciences 191 (2012) . https://doi.org/10.1016/j.ins.2011.12.028.

[50] R. J. Hyndman, G. Athanasopoulos, Forecasting: Principles and practice, OTexts. 2018.

[51] G. R. Parsons, Travel Cost Models, in: P. A. Champ, K. J. Boyle, T. C. Brown (Eds.), A Primer on Nonmarket Valuation, Springer, Dordrecht, Netherlands, 2017. pp. .

[52] Utah Division of State Parks. Park visitation data, https://stateparks.utah.gov/resources/park-visitation-data/, 2025.

[53] J. W. Smith, A. B. Miller, C. C. Lamborn, Recreationists and nearby residents' perceptions of water quality at Utah Lake (USA), Technical Report, Institute of Outdoor Recreation and Tourism, Utah State University, Logan, UT. 2023.

[54] P. H. J. Badiou, L. G. Goldsborough, Ecological impacts of an exotic benthivorous fish, the common carp (Cyprinus carpio L.), on water quality, sedimentation, and submerged macrophyte biomass in wetland mesocosms. Hydrobiologia 755 (2015) . https://doi.org/10.1007/s10750-015-2220-6.

[55] S. A. Heiskary, W. W. Walker, Developing phosphorus criteria for Minnesota lakes. Lake and Reservoir Management 4 (1988) . https://doi.org/10.1080/07438148809354373.