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Abstract

Harmful algal blooms (HABs) reduce the amenity quality and perceived safety of coastal and freshwater resources. Events trigger avoidance behavior by residents and visitors and contribute to broader economic losses. Managers need economic welfare measures that correspond to the intensity categories used in public advisories. We quantify how advisory-defined HAB risk alters the expected value of outdoor recreation trips in South Florida for two hazards: cyanobacteria (blue-green algae; microcystins) and red tide (*Karenia brevis*). We administer a split-sample contingent valuation survey in four waves (Dynata; April 2024 to March 2025; n = 4,135; 12,405 trip decisions). Respondents first identified the destination of their next South Florida trip from 11 regions and then evaluated randomized trip-cost increases and HAB intensity scenarios aligned with Florida Fish and Wildlife Conservation Commission red tide tiers and U.S. EPA microcystin benchmarks. In our preferred model, we address hypothetical bias using a stacked logit model that calibrates for choice certainty and stated attribute non-attendance. In the most conservative specification, per-travel-party willingness to pay for an overnight trip is about US$1,250 under no advisory, falls to roughly US$560–660 under low-intensity advisories, and drops to about US$200–330 under medium to high HAB intensity. These changes imply avoidance values of approximately US$600–700 per trip at low intensity and US$940–1,040 at medium to high intensity, with stated trip taking probabilities near 50% at medium/high risk. Holding trip counts fixed (valuing observed trips only) and excluding substitution, a back-of-the-envelope calculation for Lee County, FL visitation over a 60-day event window suggests order-of-magnitude recreational welfare losses of US$17–58 million for cyanobacteria and US$60–103 million for red tide. These intensity-specific estimates provide transferable inputs for benefit–cost analysis of South Florida water-management operations and nutrient-reduction policies.

Keywords: harmful algal blooms, contingent valuation method, hypothetical bias, attribute non-attendance, choice certainty, willingness to pay

1. Introduction

Harmful algal blooms (HABs) represent a significant worldwide environmental and economic threat. These blooms generate both market damages (lost tourism revenue, commercial fishing losses) and non-market welfare losses via degraded ecosystem services. Further, the absence of markets for recreational water quality complicates benefit-cost analysis of management interventions. While the debate exists related to the global bloom trends (Anderson et al. 2021, Hallegraeff et al. 2021), there is strong evidence that climatic changes and anthropogenic stressors influence the frequency and severity of HAB events (Anderson et al. 2021; Griffith & Gobler, 2020). In South Florida, these multi-scalar pressures converge. The region's management challenge stems from both regional water management operations through the Central and South Florida Project and local land use decisions, including agricultural practices, high coastal urban density, and widespread reliance on septic systems. This setting creates a need to quantify the marginal welfare losses associated with varying HAB intensities, which can provide a critical input for evaluating the trade-offs inherent in both water management and land use policies. In this context, it is important to examine individuals' responses to intensity-based measures of bloom risk. As this study elicits expected changes in recreational behavior, the valuation must align with the way information is communicated to the public. HAB intensity categories used in advisories and management bulletins provide the signals on which individuals base trip decisions, whereas on-site conditions may not be known to the user at the planning stage for individuals making their site trip decisions. Linking changes in trip-taking behavior and willingness to pay to these publicly communicated intensity levels therefore offers a conceptually consistent and policy-relevant basis for estimating welfare losses.

Empirical evidence highlights the role that water management operations play in two distinct exposure pathways for South Florida communities. First, managed discharges transport cyanobacteria (blue-green algae [BGA]) and their associated toxins (microcystins) from Lake Okeechobee into estuaries (Kramer et al. 2018, Rosen et al 2017). Second, these large pulses of nutrient-rich freshwater alter coastal salinity and can fuel nearshore intensity and persistence of otherwise naturally occurring red tide blooms (Karenia brevis) (Heil & Muni-Morgan, 2021; Medina et al. 2022; Phlips et al. 2023; Tomasko et al. 2024). This land-sea coupling can exacerbate the impacts, which compounds well-documented economic losses across fisheries, health, real estate, and tourism (Larkin & Adams, 2007; Béchard, 2020a; Béchard, 2020b; Béchard, 2020c; Béchard, 2021; Alvarez et al. 2024). From an economic perspective, recreators treat water bodies as quality-differentiated goods. In this context, increasing HAB intensity degrades site quality, influencing users' expected utility from site visits. These changes in expected utility trigger defensive behaviors among users (site substitution, temporal avoidance, activity modification) that generate welfare losses even when recreators successfully avoid direct exposure. For both red tide and blue green algae, economic behavior and welfare losses are driven by bloom intensity as communicated through public advisories, such as Florida Fish and Wildlife Conservation Commission's (FWC) cell count-based categories for red tide and public advisories for cyanobacteria based on federal health advisory benchmarks from the U.S. Environmental Protection Agency (EPA). Understanding the public's willingness-to-pay (WTP) to avoid HABs at different intensity levels can provide essential evidence to support water management decisions. Damage estimates that treat HABs as a discrete event fail to capture the potential non-linear welfare responses observed across different levels of intensity. Our intensity-specific approach addresses a key research priority identified by Adams et al (2018), since few studies have investigated how HAB severity affect economic damages.

This study applies contingent valuation method (CVM) to estimate recreation demand conditional on HAB intensity. WTP to avoid changes in risk from baseline to elevated HAB levels for overnight trips to South Florida are then estimated. Our application makes three primary contributions. First, we develop policy-relevant, intensity-based damage estimates aligned with public health and advisory thresholds used by government agencies. This provides managers with economic estimates that can be applied in benefit-cost analyses of management scenarios under varying HAB intensities. Second, our split-sample CVM design enables welfare comparisons between HAB type, specifically cyanobacteria and red tide, within a single framework. In South Florida coastal areas susceptible to both hazards, respondents are randomly assigned to a valuation scenario for either red tide or cyanobacteria. In coastal areas exposed only to red tide, all respondents receive the red tide scenario. This allows for a robust comparison of damages between two distinct hazards. Third, we mitigate hypothetical bias by incorporating *ex post* certainty calibrations (Penn and Hu, 2023) and accounting for Stated Attribute Non-Attendance (SANA) (Lew and Whitehead, 2020), which reduce baseline WTP estimates by 15-38% and improve behavioral realism. We find that WTP for overnight trips falls 40-56% under low-intensity risk conditions and by roughly 70-85% under medium-to-high intensity risk events. Model results demonstrate substantial welfare losses that vary across the intensity gradients.

This paper is structured as follows: Section 2 provides background on South Florida HABs and reviews prior economic evidence. Section 3 presents the theoretical framework and survey design. Section 4 reports results, and Section 5 concludes.

2. Background (condensed; South Florida first; explicit baseline vs. exacerbation)

2.1. Hazard definitions & how the public sees "intensity"

This study addresses two distinct HAB hazards prevalent in South Florida: red tide and blue-green algae. The naturally occurring marine dinoflagellate *Karenia brevis* (red tide) produces brevetoxins that can aerosolize, causing respiratory irritation, fish kills, and shellfish harvesting closures that lead to avoidance across a wide range of activities in the coastal zone (Diaz et al., 2019; Fleming et al., 2011; Hoagland et al. 2009). Most *K. brevis* blooms typically initiate on the mid-West Florida Shelf, with reoccurring impacts on Florida's Southwest coast. Events on the Atlantic coast occur infrequently and usually reflect advection of Gulf waters through the Florida Straits and into the Florida Current/Gulf Stream (Hu et al., 2022; Weisberg et al. 2019).

The Florida Fish and Wildlife Conservation Commission (FWC) classifies the severity of *K. brevis* through the following cell count intensity categories: background ($\leq$ 1000 cells L^{-1}), very low ($1{,}000 - 10{,}000$ cells L^{-1}), low ($10{,}000 - 100{,}000$ cells L^{-1}), medium ($100{,}000 - 1{,}000{,}000$ cells L^{-1}), high (>1,000,000 cells L^{-1}). The Florida Department of

Agriculture and Consumer Services (FDACS) closes shellfish harvesting areas at $\geq 5{,}000$ cells L^{-1}. While red tide is a natural, baseline risk in Gulf of Mexico water, the nearshore exacerbation of this risk refers to the potential for freshwater nutrient pulses or land-based nutrient sources to increase the severity and persistence of blooms (Heil & Muni-Morgan, 2021; Medina et al. 2022). In our survey instrument, we display four FWC-aligned tiers (very low, low, moderate, high) based on the numeric cutoffs in Table 1 (red tide column). From perspective of recreational behavior, these communicated intensity levels enter recreators' decisions as quality attributes that determine site choice and trip timing. It is important to account for the fact that behavioral responses do not only depend on actual water quality conditions, but also in response to the ways in which risk information is processed and communicated to recreators through official agency channels and the media.

Cyanobacteria (blue-green algae) blooms are primarily a freshwater or estuarine phenomenon characterized by visible scums, odors, and the production of microcystins that pose health risks (Huisman et al. 2018; Igwaran et al. 2024; Schaefer et al., 2020). When referring specifically to cyanobacteria, these blooms are often described as an occasional upper water column phenomenon, as the buoyant colonies frequently aggregate at the surface to form scums during calm conditions. Florida has no official statewide intensity standard for blue-green algae blooms but, in practice, public advisories are often anchored to the U.S. Environmental Protection Agency's (EPA) 8 $\mu g \cdot L^{-1}$ recreational benchmark for microcystins (Schaefer et al., 2020). Accordingly, we display the following three microcystin tiers in our survey instrument: Low (<8 $\mu g\ L^{-1}$), Moderate (8-16 $\mu g\ L^{-1}$), and High (>16 $\mu g\ L^{-1}$), as shown in Table 1 (Blue-Green Algae column).

2.2. South Florida hydrology & operations

South Florida's hydrology is dominated by the Central & South Florida (C&SF) Project, a regional water management system of canals, levees, and control structures that regulate the flow of water within 16 counties in the South Florida Water Management District (SFWMD). In the northern portion of the C&SF project, water operations dictate the timing and volume of releases from Lake Okeechobee into the Caloosahatchee and St Lucie estuaries. While less common, discharges may also influence the Lake Worth Lagoon in Palm Beach County.

These C&SF operations have established two key pathways for HAB exposure. First, the cyanobacteria pathway is direct. Episodic managed discharges can transport bloom biomass and microcystins from the lake into downstream rivers, estuaries, and near-coastal waters. These discharges cause high-visibility events that impact recreation and trigger health advisories (Schaefer et al. 2020; Paudel et al, 2020). Second, the red tide pathway manifests itself through the exacerbation of events. Freshwater nutrient pulses from discharges can support the nearshore persistence and severity of *K. brevis* blooms whose initiation remains an offshore process in the Gulf of Mexico (Heil, 2021; Medina et al. 2024). We therefore frame this as management's potential to incrementally worsen, but not create, red tide risk.

While the underlying hydrodynamic and ecological pathways are complex, recreational behavior is primarily mediated by both direct contact risk and the dissemination of public advisory (risk) communications. Our study therefore aligns its valuation attributes directly with these agency thresholds.

2.3. From Intensity Communication to Valuation Attributes

To ensure policy relevance, our study design attributes align with agency risk communication practices. For red tide, we adopt FWC's official intensity categories. Four FWC intensity categories (very low, low, medium, high) were used to define the risk levels presented in our valuation scenarios (Strumpf et al., 2022). For cyanobacteria, no official state categories exist. We develop scientifically grounded tiers that are anchored to EPA's recreational microcystin benchmark (Schaefer et al., 2020). Table 1 reports the numeric thresholds used to identify increasing intensity. This approach is critical because respondents recognize and act on these categories, which ensures our study yields policy-relevant welfare measures grounded in the public's actual decision-making framework (Boudreaux et al. 2023; L'Ecuyer-Sauvageau et al., 2019). This enables more behaviorally realistic applications for benefit-cost analyses targeted at management scenarios that alter HAB intensity through operational or regulatory interventions. Moving up or down these intensity tiers changes recreation quality and availability, which in turn alters economic welfare.

2.4. Economic impact channels & Prior Evidence

HAB events generate a wide spectrum of economic damage. Market impacts include direct revenue losses in tourism, hospitality, and commercial fisheries and also indirect negative impacts to property values in local housing markets (Larkin & Adams, 2007; Morgan et al., 2009; Wolf et al. 2019; Wolf and Klaiber 2017; Ferreira et al. 2023; Alvarez et al., 2024). Non-market impacts – the focus of this study – involve the degradation of environmental conditions that influence economic behavior occurring outside of traditional markets, such as recreational quality and availability for activities like beachgoing, boating, and fishing. HAB related non-market valuation studies in Florida cover a range of topics including health, recreation, and real estate (Moeltner et al. 2023, Alvarez et al. 2019; Béchard, 2021). These HAB impacts can lead to strong site avoidance behavior in response to advisory communications (Boudreaux et al., 2023). Further, these impacts can become embedded in asset prices through capitalization, where property values near affected waters decline in response to HAB risk (Wolf and Klaiber 2017, Bechard, 2021; Zhang, Phaneauf, & Schaeffer, 2022). Studies have also investigated health impacts that include respiratory distress from red tide aerosols and dermal/gastrointestinal issues from cyanobacteria, resulting in medical costs and productivity losses (Grattan et al. 2016; Igwaran et al., 2024).

There is a robust evidence base demonstrating economic consequences of HABs in Florida, but methodological limitations constrain its policy application. Revealed preference studies have documented significant revenue and sales losses for coastal businesses during red tide events (Larkin & Adams, 2007; Morgan et al., 2009; Morgan et al. 2011; Béchard 2019; Béchard 2020; Alvarez et al. 2024). Many of these studies are considered market-price proxy studies as they quantify market losses using measures such as sales, receipts, or attendance. These studies generally study changes in economic activity in response to HABs and are valuable for understanding economic responses or the magnitude of events but have more limited applications to benefit cost analysis.

While these studies document substantial impacts, most do not provide welfare measures across the full risk- intensity gradient. One noted exception is Alvarez et al. (2024), who use market-price proxies to develop the first statewide, intensity-based estimates. They find a non-linear response to HAB intensity during the 2018 HAB event noting the likely influence of behavior factors such as substitution effects and social contagion in driving outcomes. Hunter et al. (2012) demonstrate that perceived rather than objective risk drives HAB-related WTP estimates, indicating that non-linear welfare responses may reflect risk perception thresholds as HAB intensity increases.

Alvarez et al. (2024) argue that non-linear patterns align with social amplification of risk theory (Kasperson et al. 1988), where "biophysical elements of hazards interact with psychological, social, institutional, and cultural processes in ways that may amplify or attenuate public responses to risk or risk event." The mechanisms behind these non-linear patterns represent a critical gap in the economic understanding of HAB risks. Establishing intensity-based measures appropriate for benefit cost analysis provides a key component for filling this gap but a larger understanding of the economics of HABs depends on understanding the mechanisms driving behavior.

A small literature studies the influence of HABs on recreation demand via revealed and stated preference methods. While revealed preference studies dominate the economic literature, most come in the form of market-price proxies (Carias et al., 2025). Fewer studies investigate the influence of HABs on recreation demand using travel cost models. In the US, there are two RP travel cost applications. Alvarez et al. (2019) study the influence of the 2018 blue-green algae discharges from Lake Okeechobee on boat-ramp closures, finding an average loss of $17.26 per trip and $30-$40 loss per trip after adjusting for site-specific lost trips. Wolf et al (2019) estimate the influence of blue-green algae exposure and closures at Lake Erie, finding intensity-based losses of $2.60-$3.44 per trip for severe blooms on average and $5.28-$9.27 losses on average for closure of western-basin sites. Wolf et al (2019) find significantly higher losses attributed to anglers compared to beach-goers, showing the importance of activity type I calculations. For longer, multi-day trips, for individuals owning second homes in Finland, Huhtala & Lankia (2012) find that HABs reduce the consumer surplus of trips by roughly 40%.

For stated preference studies, most recreation-related study sites are in the Great Lakes and Europe. Multiple studies use HAB intensity or exposure as design attributes. Zhang & Sohngen (2018) estimate Lake Erie anglers are willing to pay $8-$12 per trip to avoid one extra mile boating through a bloom, $52-$60 per trip to avoid one hour of HAB-impacted boating, and $77-$114 for improved water clarity during their trip. Boudreaux et al. (2023) use stated preference methods to estimate a willingness-to-drive to avoid HABs. They find a large aversion to HABs with respondents willing to drive an additional 260 miles when a HAB warning is in effect and 31 additional miles six days after a warning is lifted. What does this show? Although Florida has a long history of HAB events, we know of no studies estimating the impact of HABs on recreation.

2.5. Justification for the Stated Preference Approach

In their review of the existing literature on the economic effects of HABs, Adams et al. (2018) indicate that there are methodological inconsistencies across studies. They suggest that, from a management and policy perspective, comprehensive economic valuations need clear intensity-based categories and better alignment of risk communication. Also, Carias et al. (2024) review the existing literature and highlight that the majority of studies use market-based proxies (like decreased sales or revenue indicators) but WTP measures for nonmarket effects are under-represented. We employ the CVM grounded in random utility theory (Hanemann 1984) to recover welfare estimates across intensity levels for both red tide and cyanobacteria. Our risk-intensity measures are aligned with agency risk-communication practices, anchored to FWC and EPA benchmarks. Ultimately, estimating per-trip welfare effects due to changes in risk intensity, by different HAB type, helps fill the gaps in the literature.

Florida represents a region frequently impacted by HABs and no recreation demand studies exist that can account for HAB intensity in benefit-cost applications. To improve behavioral realism, our econometric models incorporate Stated Attribute-Non-Attendance (SANA), which accounts for respondent inattention to cost or risk attributes and calibrates WTP to more plausible magnitudes (Lew & Whitehead, 2020). The resulting welfare estimates are aligned with agency thresholds and directly usable in the benefit-cost analysis of water management policies (Hanemann, 1984). The specific implementation of this approach is detailed in the following sections.

3. Survey Design

We developed the survey using Qualtrics, Inc software. Four waves of the survey were administered to respondents through the Dynata panel. Wave 1 included both a pretest and follow-up survey, conducted between April 26 to May 8, 2024. The remining three waves were administered between August 2024 and March 2025. Different standard practices are used to improve the quality of the data, such as removing responses from those who answered inconsistently to household income questions posed at different points in the survey. Responses are also removed for inconsistencies regarding age and place of residence. In total, 8,191 Dynata panelists competed one survey wave.

The survey targeted those who participate in recreation activities across South Florida. While the focus of the survey is on Florida residents, a stratified sampling approach included residents from every state in the U.S. The majority of the sample are Florida residents (73.3%) with the other most-sampled states being California (4.8%), New York (4.1%), and Texas (3.1%). Table 2 provides a breakdown of respondent demographics across all waves.

Most respondents (57.4%) are aged between 18 and 44 years. The mean age is 42.5 years. Slightly under half (48%) are female. 47% of respondents earned over $75,000 in pre-tax income in 2023. About one quarter of respondents have a bachelor's degree and 18% have earned a master's degree or higher.

The survey asked respondents a series of revealed (actual) preference (RP) and stated (expected) preference (SP) trip questions regarding the number and location of RP and SP recreation trips to the south Florida area. All RP/SP trip questions are posed over a 3-month period. With respect to RP trips, respondents were asked the types of recreation activities they participated in on their most-recent trip. The most popular recreation activity is a beach recreation trip (53.6%) that could include swimming, sunbathing, picnicking, beach sports or walking on the beach. Wildlife observation (24.1%) and saltwater fishing (23.7%) are the next most popular, followed by sailing (19.2%) – including boating, jet-skiing, waterskiing, or wake boarding – kayaking (15.5%), and scuba diving (15.3%).

Those that participated in saltwater fishing were also asked how they primarily fished. Slightly over half of those respondents (51.3%) report fishing from the shore with 25.4% reporting taking a charter boat trip and 23.3% taking a private or rental boat. Further, for those taking a private or rental boat trip, the majority (81.4%) fished in in the ocean (as opposed to the sound, river, or bay). Of this group, most (50.2%) fished offshore (defined as more than 3 miles from the shore).

4. Stated Preference Approach

For SP trips, we elicit information on the next outdoor recreation trip that respondents think they will take in South Florida. Here, respondents were presented with a map of South Florida and asked to identify the expected location of their next trip. The map breaks out the south Florida area into 11 regions, ranging from Charlotte County on the Gulf coast, down to the Keys area, and up to St. Lucie and Martin counties on the east coast (see Figure 1).

Table 3 provides a breakdown of the chosen locations of the respondents' next trip, by survey wave. The most popular destination across all waves for the next trip is Palm Beach County (19.9% across all waves). A further 11.8% of respondents expect to take their next trip to Marco and Naples, with 10.3% expecting to go to Middle and Lower Keys. The Ten Thousand Islands region (3.4%) is expected to be the least-frequented area for respondents' next trip.

Respondents are also asked about the number of nights stayed, the size of the travel party and the amount of money that will be spent on this planned next trip. About two-thirds of the next trips are overnight trips and the average trip length is a 3-night stay, with two nights as the modal response. Most (58.0%) stayed in a hotel or motel, and on average, there are 3 people in the party, spending \$910 per trip. The highest spending category is lodging with an average of \$197.90 on the most-recent trip.

Respondents are then told: "Trip costs such as travel and other expenses change over time. For example, gas prices fell from 2014 to 2016 and rose from 2020 to 2022. Overall inflation was high in 2021 and 2022. Now suppose that travel and other expenses are $A\%$ higher in South Florida." A is one of six percentage values that is randomly presented to respondents: $A = 25, 40, 55, 70, 85, 100$. By survey design, the percent increase is also converted to the corresponding change in dollar trip cost. Respondents are then told: "Based on your expected trip costs of $\{S\}$, this would mean that the cost of your trip would increase by $\{S \times A\%\}$ to $\{(S \times A\%) + S\}$." S is the amount of money that respondents think they will spend, obtained from the answer to the earlier question. Respondents are then asked: “Would you still plan to go to $\{SF_j\}$ on your next trip?” where SF_j is the location of the next South Florida outdoor recreation trip obtained from the earlier question, $j = 1, \ldots, 11$.

Depending on the respondent recreation site choice, survey respondents are presented with one of two hypothetical scenarios for a red tide event or BGA bloom. Dependent on the treatment received, respondents are first provided with information regarding either red tide events or BGA blooms and their location and connection to nutrient discharges. They are further informed about the impacts of red tide events or BGA blooms on fish kills and other marine animals, and the potential respiratory implications to humans through exposure to airborne toxins. Of those that expect to take a trip in the next 3 months, 76.0% received the red tide treatment and the remaining 24.0% received the BGA treatment.

Respondents were asked a series of questions regarding their perceptions of red tide and BGA Respondents were first asked to state their level of concern regarding red tide or BGA on a five-point Likert scale, ranging from “1=not concerned at all” to “5=very concerned”. 68.62% and 69.1% of respondents are concerned or very concerned about red tide events and BGA blooms, respectively. With regard to health impacts, on a five-point Likert scale ranging from “1=no symptoms” to “5=severe symptoms”, 18.2% rate the health impacts experienced during a red tide event as severe with 10.3% indicating no symptoms. For BGA, 22.9% of respondents indicate severe health symptoms and 8.7% indicate no symptoms.

With respect to respondent perceptions and attitudes towards red tide events and BGA blooms (on a five-point Likert scale ranging from “1=strongly disagree” to “5=strongly agree”), Table 4 summarizes percent responses for those that either agree or strongly agree to the statement for both those receiving the red tide or BGA treatment.

In terms of personal experiences with red tide events, 25.5% of respondents have never seen a red tide event in South Florida. A further 44.6% have sometimes seen a red tide event, while 18.2% and 6.1% have often seen or have always seen an event, respectively. With respect to BGA blooms, 20.3% have never seen a bloom, while 44.0% have sometimes seen one and 9.4% always see them.

For those that have seen red tide or BGA blooms, a follow-up question asks whether respondents experienced any symptoms from a list of potential options (respondents could click any symptom that applied). With respect to red tide, the most common symptoms experienced are eye irritation (24.0%), respiratory irritation (20.0%), and throat irritation (19.2%). Just under 23% of respondents experienced no symptoms.

For BGA, the most-commonly experienced symptoms are nausea (42.2%), itchy eyes (19.3%), sore throat (14.4%), and skin rashes (11.7%). Almost 30% of respondents experienced no symptoms. The distribution of self-reported exposure frequencies for both hazards is summarized in Table 5.

If respondents received the red tide treatment, they are then told that they will be asked what they would do if the site that they chose for their next trip is dealing with a red tide problem. They are informed that there are options, such as “taking the trip as you don’t think the problem will be an issue”, “taking a trip to another South Florida recreation site”, or “decide to do something else”.

After presenting information about the red tide problem in the Gulf of Mexico and East Coast of Florida, we presented respondents with a table that described the health and environmental impacts of very low, low, medium and high red tide intensities. Then we asked: "Suppose that $\{SF_j\}$ is/are experiencing a {very low, low, medium, high} red tide problem. Would you still plan to go to $\{SF_j\}$ on your next trip?" One of the red tide risk intensities is randomly chosen for each respondent.

5. Data and Modeling

In this section we estimate models to test for differences across waves and environmental risk. By survey design, we asked a number of questions that allow for sensitivity analysis and robustness checks. Certainty follow-up questions were asked and are used to recode the dependent variable from yes to no if the respondent is uncertain about their yes response (Penn and Hu 2023). Stated attribute non-attendance questions ask respondents about how much they paid attention to various attributes, or how important various attributes were, when answering choice questions (Lew and Whitehead 2020). Research has shown that inattention to the cost attribute will inflate willingness to pay estimates and inattention to the quality attribute will manifest as insensitivity to scope. We estimate four combined models: raw yes responses with and without stated attribute non-attendance and certainty recoded yes responses with and without stated attribute non-attendance.

We use the four-waves data presented in the previous sections with one caveat. Recall that we ask respondents about how much they planned to spend on their planned recreation trip and then use this amount to generate an additional trip cost variable. Preliminary analysis of the combined data found that there were only minor differences in the willingness to pay for day and overnight trips. This prompted an investigation into the quality of the spending variable. We found that the 99th percentile of spending for day trippers was \$3000 with many reporting the largest possible amount of \$5500. This suggests that respondents may be planning a major capital purchase on their day trip and/or were being careless when reporting their potential spending. Eleven percent of respondents reported being very or somewhat uncertain about their spending forecasts.

After removal of 316 spending outliers, 7% of the data, we re-estimate the spending regression model and find that the coefficient of determination (R^2) increases from 0.28 to 0.37, indicating significantly higher reliability in the data.[1] Before removal of outliers, the mean of trip spending

[1] Given the potential sensitivity of our results to the spending variable we identified and removed outliers to determine if the performance of the recreation demand models improved economically and statistically. We use a regression-based approach to identify outliers. We first estimate a regression model with trip spending as the dependent variable. We find that spending increases with the number of nights stayed on an overnight trip, with the number of people in the travel party, with income, with age (at a decreasing rate), for out-of-state visitors and for charter and private boat fishing trips. From this model we calculate the Cook's Distance (D) statistic for each observation in the data. Cook's Distance is a measure of how much regression coefficients

is $1016 for overnight trips and $319 for day trips. After removal of outliers, the mean of trip spending is $833 for overnight trips and $254 for day trips. After removing outliers the performance of the CVM regression models significantly improves so these are the results that we report below.

With this sample the percentage of yes responses falls from 84% when the cost increase is 25% of trip spending to 60% when the cost increase is 100% of trip spending (Table 6). The differences in frequencies at each percentage increase are statistically significant at the $p<0.01$ level ($\chi^2 = 138.09$ [5 df]). For respondents who answer yes to the trip question we present a follow-up question: "Given the trip choice that you just made, on the following scale between 1 (very uncertain) to 5 (very certain), how certain are you that you would make that trip choice?" Eighteen percent of yes respondents were very or somewhat uncertain or neutral about their answers. We recode these responses to a no response (YesCert in Table 6-7). The percentage of somewhat or very certain yes responses is 67% when the cost increase is 25% of trip spending and falls to 49% when the cost increase is 100% of trip spending. The differences in frequencies at each percentage increase are statistically significant at the $p<0.01$ level ($\chi^2 = 74.67$ [5 df]).

We next consider how the yes responses differ with the health-risk variables for the combined sample. The percentage of yes responses falls from 74% when the red tide health risk is very low to 36% when the risk is high (Table 7). The differences in frequencies at each percentage increase are statistically significant at the $p<0.01$ level ($\chi^2 = 343.79$ [3 df]). The percentage of certain yes responses is 61% when the risk is very low and this falls to 28% when the risk is high. The differences in frequencies across risk categories are statistically significant at the $p<0.01$ level ($\chi^2 = 261.62$ [3 df]). Results are similar for blue green algae health risks. The percentage of yes responses falls from 77% when the blue green algae health risk is low to 49% when the risk is high. The percentage of certain yes responses is 62% when the risk is low and falls to 37% when the risk is high. Both differences are statistically significant at the $p<0.01$ level ($\chi^2 = 62.37$ and $\chi^2 = 53.36$ [2 df]).

5.1 Trip-taking models

Suppose that consumers have a quasi-concave, monotonic utility function defined over recreation trips, x (with baseline cost, p, and quality, q), and consumption of a numeraire composite commodity, h, with $p_h = 1$. The resulting indirect utility function depends upon trip quality and numeraire consumption: $v(q, y-p)$, where y denotes income. If the consumer is observed taking the trip under conditions q then $v(q, y-p) > v(y)$. When faced with additional trip cost, c, the consumer will continue to take the trip if $v(q, y-p-c) \geq v(y)$, where the trip cost is less than the reservation price (implicitly defined as $x(\bar{p}, q) = 0$), $p + c < \bar{p}$. When faced with a degradation in trip quality the consumer will continue to take the trip if $v(q', y-p) \geq v(y)$,

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change if you remove each observation. We follow a standard rule of thumb in identifying outliers. If $D > 4/n$ then it is removed.

where $q > q' > \bar{q}$, and $\bar{q}$ is the reservation quality for a given price, $x(p, \bar{q}) = 0$.[2]

The theoretical model can be operationalized empirically following Hanemann (1984) and Loomis (1997). The individual utility from the choice is expected to be increasing in quality and income (and decreasing in price). Let the utility from alternative j be denoted as $v_j(q, y) + \varepsilon_j$, where v_j is the non-stochastic portion of utility for alternatives $j = 0{,}1$ (i.e., $x = 0{,}1$), and ε is the corresponding error term. The random utility model assumes that the individual chooses the alternative that gives the highest utility, $\pi_1 = \Pr(v_1 + \varepsilon_1 > v_0 + \varepsilon_0)$, where π_1 is the probability that the respondent would choose alternative $j = 1$. The probability can be rearranged to show that it depends on the difference in utilities, $\pi_1 = \Pr(v_1 - v_0 > \varepsilon_0 - \varepsilon_1)$, relative to the difference in error terms.

If the indirect utility function is assumed to be linear-in-parameters, $v = \beta + \beta_q q + \beta_y y + \varepsilon$, then the difference in utility for the first two trip scenarios (where quality is constant and the trip cost changes) is $\Delta v = \beta_1 + \beta_q q + \beta_y(y - p - c) - [\beta_0 + \beta_q q + \beta_y(y - p)] + (\varepsilon_1 - \varepsilon_0)$ and $\Delta v = \tilde{\beta} - \beta_y c + \tilde{\varepsilon}$, where $\tilde{\beta} = \beta_1 - \beta_0$, and $\tilde{\varepsilon} = \varepsilon_1 - \varepsilon_0$. Under the linear-in-parameters structure, quality, income and baseline trip cost (p) drop out of the differenced utility equation. The difference in utility for the third scenario where site quality changes is $\Delta v = \beta_1 + \beta_q q' + \beta_y(y - p - c) - [\beta_0 + \beta_q q + \beta_y(y - p)] + (\varepsilon_1 - \varepsilon_0)$ and $\Delta v = \tilde{\beta} + \beta_q(q' - q) - \beta_y c + \tilde{\varepsilon}$, where c is zero for the initial stated preference question in this scenario.

Estimation of the parameters is achieved by stacking the change in indirect utility functions considering the $t = 3$ observations (choice occasions) for each respondent, $i = 1, \ldots, N$, $\Delta v_{\mathrm{it}} = \tilde{\beta} + \beta_y c_{\mathrm{it}} + \beta_q q_{it} + \tilde{\varepsilon}_{\mathrm{it}}$ when utility is linear. Assuming ε are drawn from a joint logistic distribution, the probability that individual i will choose to take the trip in occasion t is

$$(1) \qquad Pr(x_{\mathrm{it}} = 1) = \frac{1}{1 + exp(-\Delta v_{it})}$$

In general, if the estimated utility model is $\Delta v = \tilde{\beta} - \beta_q q - \beta_y c$, where q is a quality vector, then the willingness to pay (WTP) for a recreation trip with baseline quality is $WTP = -\tilde{\beta}/\beta_y$. This is the mean (and median) WTP estimate where respondents are indifferent between taking the trip or not, and can be found by solving for the price that leads to indifference, $\pi(x = 1) = 0.50$, in the logit (Hanemann 1984). The willingness to pay for a trip with a red tide or blue green algae event is $WTP_q = \frac{-(\tilde{\beta} + \beta_q)}{\beta_y}$ and the difference in willingness to pay from a quality degradation is $\Delta WTP_q' = WTP_b' - WTP_q'$, where b is the base case.

5.2 Regression Models

The dependent variables for the regression models are Yes and YesCert. The independent variables include cost and the risk variables as above. We include an interaction term between

[2] The empirical model is similar to Whitehead et al. (2024) who estimate the effect of drinking water quality on coastal tourist trips.

cost and a day trip that better captures the difference between day and overnight trips relative to the overnight trip dummy variable approach. We also include dummy variables for Waves 2, 3 and 4 with Wave 1 as the baseline (i.e., Wave 1 is captured in the constant).

We estimate switching stated attribute non-attendance models. We estimate separate cost and risk coefficients for those attending and those not attending to each attribute. In other words, an attribute has a coefficient β_1 = 1 when the attribute is attended to and $\beta_0$otherwise. Thirteen percent of respondents answered that the trip cost amount was 1 (not very important) or 2 on a 5-point scale with 5 equal to very important. Similarly, thirteen percent of respondents answered that the risk level was 1 or 2 on a 5-point scale. These are the respondents coded ANA=0 in the stated ANA regression models. Other codings were attempted, for example we also included those who answered 3 and non-attending, but this one fit the data best.

In the baseline Model 1 (YES, no ANA), survey respondents are less likely to continue taking the trip as the trip cost increases (Table 8). The cost and day trip interaction term increases the day trip cost by about 79% (making the resulting day trip WTP lower than the overnight trip WTP).[3] Each of the health risk coefficient estimates are negative and statistically different from zero, with the coefficients decreasing (becoming more negative) as the risk increases. The dummy variables for waves 3 and 4 are positive and statistically different from zero suggesting that WTP for a trip is higher in the Fall and Winter.

The stated ANA (SANA) Model 2 performs better statistically with an AIC statistic lower than that of Model 1. The attending coefficient vector is similar in sign and statistical significance to the corresponding coefficients in Model 1. Among the attributes, the attending coefficients are between 4% and 10% larger relative to Model 1. Larger (in absolute value) cost coefficients decrease WTP and more negative risk coefficients decrease WTP. The non-attending coefficient vector performs relatively poorly. The non-attending coefficients are significantly closer to zero relative to the attending coefficients and three of the non-attending coefficients are not statistically different from zero.

The pattern of results in Models 3 and 4 are similar to that of Models 1 and 2. In Model 3 (YESCERT, no ANA), survey respondents are less likely to continue taking the trip as the trip cost increases and the cost and day trip interaction term is negative and statistically significant (Table 9). Each of the health risk coefficient estimates are negative and statistically significant with the coefficients becoming more negative as the risk increases. The certainty correction typically effects the regression constant and we find that here. The Model 1 constant is 31% higher than the Model 3 constant. We also find that the cost by day trip interaction coefficient is 41% higher (in absolute value) in the YESCERT model.

The stated ANA (SANA) Model 4 performs better statistically with an AIC lower than that of Model 3. The attending coefficient vector is similar in sign and statistical significance to the corresponding coefficients in Model 3, but the differences are smaller than in Table 8. Among the

[3] In contrast, in the same model without outliers removed the cost and day-trip interaction coefficient is not statistically different from zero, suggesting that day trips and overnight trips are of equal value.

attributes, the attending coefficients are between 0% and 7% larger. The non-attending coefficient vector performs relatively poorly. The non-attending coefficients are significantly closer to zero relative to the attending coefficients with one exception: the non-attending cost by day trip coefficient is 53% larger (in absolute value) relative to Model 3.

5.3 WTP Estimates

We calculate baseline (no risk) WTP for each wave and report these by wave in Tables 10-11. For the HAB risk scenarios in Tables 10-11, we evaluate WTP at Wave 4 so the risk scenario WTP levels are presented on a common baseline. The Hanemann (1984) formula produces several negative WTP estimates as the probability of a trip falls below 50% when the additional trip cost is zero and health risks are medium and high. To avoid negative WTP we use the Hanemann (1989) formula: $WTP = (-\frac{1}{\beta_y}) \times \ln\left(1 + \exp(\tilde{\beta})\right)$. This increases the base case WTP estimate by 6% and the differences are not statistically significant. In our application, WTP is interpreted as per-trip consumer surplus for taking the planned trip under the stated conditions. Avoidance values (ΔWTP) are computed as the difference between baseline WTP and tier-specific WTP.

In Model 1, WTP for an overnight-trip ranges from $1535 to $1728 (Table 10). With very low red tide risk WTP falls to $981 and with low risk WTP is $903. WTP is $474 and $318 with medium and high red tide risk. With low blue green algae risk WTP falls to $1109. WTP is $565 and $528 with moderate and high blue green algae risk.

The pattern of results for the attending overnight trip WTP estimates in Model 2 are similar to those in Model 1. But once the non-attending respondents are purged the baseline WTP estimates are 6% lower and between 8% and 17% lower in the health risk scenarios when WTP is positive and statistically different from zero. WTP estimates in the non-attending class are much larger than those from Model 1. The baseline WTP estimates are over 100% higher and WTP with health risks are 154-290% higher than those from Model 1.

The overnight trip WTP estimates from the certain yes models are lower relative to the baseline model as expected (Table 11). WTP in the certainty adjusted Model 3 are 15% to 38% lower than those in Model 1. WTP estimates from the attending coefficient vector in Model 4 are between 6% and 15% lower than in Model 3. WTP estimates from the non-attending coefficient vector in Model 4 are between 106% and 227% higher than in Model 3.

The pattern of WTP for a day trip is similar across scenario and models as WTP for an overnight trip. Since the only difference in the two estimates is the coefficient on cost by day trip interaction term in the denominator, WTP for a day trip will be a constant proportion of WTP for an overnight trip. In Models 1 and 2 this proportion is 57% for Model 1 and the attending coefficient vector for Model 2 and 41% for the non-attending vector of Model 2. The proportion of day to overnight WTP is 47% for Model 3, 50% for the attending coefficient vector for Model 4 and 20% for the non-attending vector of Model 4.

5.4 Aggregate Benefits

In this section, we develop aggregate, back-of-the-envelope avoidance benefit (welfare loss) estimates for blue green algae and red tide events in Lee County, Florida by scaling per-trip willingness to pay estimates to overnight visitation based on Lee County Visitor Tracking Reports (Downs & St. Germain Research, Jul-Sep 2024 [Q3]; Oct-Dec 2024 [Q4]). We pair Q3 (Jul-Sep 2024) visitation with survey Wave 2 estimates and Q4 (Oct-Dec 2024) visitation with survey Wave 3 for consistency in seasonal timing. Because wave effects enter additively in Model 4, per-trip avoidance values are invariant to the wave intercept. We apply the same ΔWTP estimates when scaling to Q3 (Wave 2) and Q4 (Wave 3) visitation. We focus on overnight trips because day-trip counts are small in Visitor and Convention Bureau (VCB) tracking reports, which are designed to characterize the overnight visitor market and record day trips as a residual visitor segment rather than a comprehensive measure of local day activity. According to Lee County Visitor & Convention Bureau, there are about 683,300 overnight visitors to Lee County in Q3 and 858,500 overnight visitors in Q4 of 2024 (equivalently, 227,000 and 285,200 overnight travel-party trips assuming 3.01 persons per overnight party). We use Lee County as our example because it is a focal area for both Gulf coast red tide impacts and blue-green algae impacts tied to discharges from Lake Okeechobee into the Caloosahatchee system. These two periods (Q3-Q4) overlap seasonal periods when these hazards are more commonly observed in Florida. Blue green algae outbreaks are more common in the summer and early fall (Q3) and red tide most often forms in late summer and early fall and can persist into the winter (Q3-Q4).

To convert visitation into exposed recreation trips, we use water-based outdoor activity participation reported in the quarterly VCB surveys as a proxy for the share of trips plausibly affected by each hazard. For red tide, exposed trips are anchored to beach participation, yielding an activity informed exposure share of 0.64 (Q3) and 0.53 (Q4). For blue-green algae, our exposed trips are based on broader freshwater and estuarine activities, specifically fishing, water sports, nature/bird watching, and biking/hiking. Since VCB activity categories are multiple-response and not location specific, we avoid overstating exposure by down weighting participation in fishing, water sports, nature/bird watching, and biking/hiking by 25-50%. This leads to activity informed exposure shares of 0.20-0.36 (Q3) and 0.18-0.33 (Q4).

We estimate aggregate welfare effects by multiplying the per-trip avoidance value (ΔWTP) for the relevant intensity tier by the number of overnight party trips and the hazard-specific exposure share. We intend to provide these estimates for order-of-magnitude context, not a full accounting of county level damages since they also exclude trip cancellations, substitution to other sites, and behavioral adaptation.

The per-trip willingness to pay to avoid a blue-green algae event is the difference between baseline WTP for an overnight trip (evaluated at a survey waves 2 and 3) and the WTP under the relevant blue-green algae intensity tier. Model 4 (attendance only) yields per-trip avoidance values of $\Delta WTP_{BGA} \approx \$583$ (low risk), $\Delta WTP_{BGA} \approx \$912$ (moderate risk), and $\Delta WTP_{BGA} \approx \$949$ (high risk) per overnight travel-party trip. We apply these values to Lee County using quarterly overnight visitation totals from the Lee County Visitor Tracking Reports, converting persons to travel-party trips using the survey mean overnight party size (3.01). Applying an illustrative 60-day event window results in roughly 148,050 travel-party trips in Q3 and 186,010 trips in Q4. When we adjust the total number of trips using the activity-informed exposure range for outdoor recreation, we get between 29,101-53,794 exposed travel-party trips in Q3 and between 32,955-61,423 exposed travel-party trips in Q4. This implies back-of-the-envelope welfare losses of approximately \$17.0-\$31.4M (low), \$26.6-\$49.1M (moderate), and \$27.6-\$51.0M (high) in Q3, and \$19.2-\$35.8M (low), \$30.1-\$56.0M (moderate), and \$31.3-\$58.3M (high) in Q4. These estimates value observed trips only, excluding welfare implications of trip cancellation, substitution, and within-trip behavioral adaptation.

Applying the same approach to red tide, Model 4 (attendance only) estimates per-trip avoidance values of $\Delta WTP_{RT} \approx \$636$ (very low risk), $\Delta WTP_{RT} \approx \$686$ (low risk), $\Delta WTP_{RT} \approx \$964$ (medium risk), and $\Delta WTP_{RT} \approx \$1042$ (high risk) per overnight travel-party trip. Based on the same 60-day overnight travel-party trip totals (148,050 in Q3; 186,010 in Q4) and proxying exposure with beach participation from VCB quarterly surveys results in roughly 94,752 exposed trips in Q3 and 98,586 in Q4. This implies back-of-the-envelope welfare losses of approximately \$60.3M (very low), \$65.0M (low), \$91.4M (medium), and \$98.7M (high) in Q3, and \$62.7M (very low), \$67.6M (low), \$95.0M (medium), and \$102.7M (high) in Q4.

For context, transaction-based studies of the 2018 HAB events report tourism related losses of \$2.7B statewide with \$247M occurring in Lee County (Alvarez et al., 2024). Using Airbnb data, Ferreira et al. (2023) estimated \$184m in out-of-state expenditure losses and greater than \$317M in total economic output losses on the Gulf Coast. While different types of measures, they represent order-of-magnitude benchmarks for our results.

6. Conclusion

This study used the contingent valuation method to estimate the economic effects of harmful algal bloom (HAB) events on recreation demand in South Florida. This study advances understanding of the recreational costs of HABs by using a dual-hazard design to estimate welfare losses from both red tide events and blue-green algae blooms. As the management of South Florida's water infrastructure affects both bloom types through distinct but interconnected pathways, integrated valuation is essential for guiding operational and infrastructure investments. Using policy-aligned HAB risk intensity categories (Adams et al., 2018) allow the estimates from recreation demand models and associated willingness-to-pay measures to provide direct input into risk communication channels and advisory thresholds used by management agencies.

Recreation demand data were collected from four waves of online surveys through the Dynata panel from April 2024 to March 2025, targeting those who participated in recreation activities across South Florida. Respondents were asked stated preference questions regarding their next trip choice under baseline conditions, trip-cost increases and elevated HAB risk scenarios. Four recreation demand models were estimated to account for both choice certainty and attribute non-attendance. All models show that respondents are less likely to take a trip if trip-cost increases. Further, health-risk coefficients are negative and statistically significant, so elevated red tide and blue-green algae risk decrease the probability of taking a trip. Moreover, we observe a statistically significant monotonic decline in the probability of taking a trip as HAB intensity increases, for both hazard types.

Using a dual-hazard design, we provide WTP estimates for both red tide and blue-green algae treatments. Per-trip willingness-to-pay estimates decrease as bloom intensity rises. For example, in the baseline model, respondents' per-trip willingness-to-pay when faced with a very low red tide risk is $981, falling to $319 if faced with a high health risk. For blue-green algae, respondents' per-trip willingness-to-pay is $1109 at a low-risk level compared to $528 if facing a high risk. WTP measures are then adjusted when correcting for choice certainty and stated ANA. In the certainty-adjusted model, WTP estimates are 15% to 38% lower than those in the baseline model. When accounting for ANA, WTP estimates are between 6% and 15% lower than in Model 3 (choice certainty model). WTP estimates from the non-attending coefficient vector in Model 4 are between 106% and 227% higher than in Model 3. The steep welfare losses at lower HAB intensities suggest that recreational values are highly sensitive to the presence of HABs. High intensity advisories reduce per-trip WTP to roughly $200-$300 (roughly 15%-25% of baseline), implying a substantial reduction in recreational surplus for observed trips.

The divergence between our findings and more recent market-based studies illustrate the behavioral complexity of recreational users' response to HABs. Alvarez et al. (2024) find an inverted U-shaped market response to increasing red tide intensity during the 2018 Florida HAB event. While also non-linear, our monotonic welfare declines tell a different story. This discrepancy likely reflects system-wide adaptive behaviors captured in market prices as well as social amplification processes that may influence aggregate responses (Kasperson et al. 1988). Our approach measures the underlying welfare loss at each intensity level, but our model does not capture these adaptive responses or the potential for social contagion effects. At extreme HAB intensities, media coverage and social networks may trigger behavioral responses that spill over into minimally or non-effected areas. A more complete approach would account for spatial substitution, temporal behavioral adjustments, and changes in recreational activities. Further, Hunter et al.'s (2012) findings emphasize the role of risk perception in behavior response to HABs. This highlights the role of information channels in economic outcomes. This aligns with Moeltner et al.'s (2023) finding that improved HAB forecasts provide substantial economic benefits for households. Reducing uncertainty over HAB intensity may mitigate welfare losses on aggregate. More complex adaptations may lead to non-monotonic changes in aggregate welfare over the region. Future approaches should incorporate these types of dynamics through study designs that explicitly models substitution options, information, and risk perceptions.

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Figure 1. South Florida Region

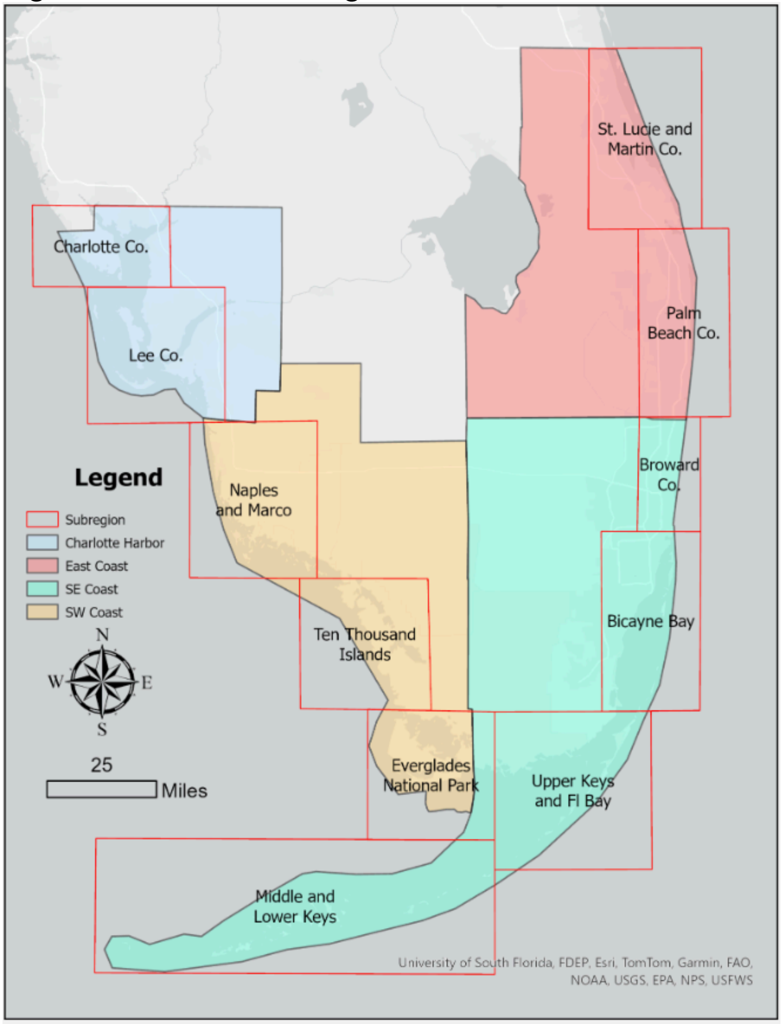

Table 1. Harmful Algal Bloom Intensities

HAB Intensity	Red Tide	Blue-Green Algae
Very Low	1,000-10,000 cells L^{-1}	---
Low	10,000-100,000 cells L^{-1}	<8 μg/L
Moderate	100,000-1,000,000 cells L^{-1}	8-16 μg/L
High	> 1,000,000 cells L^{-1}	>16 μg/L

Table 2. Survey Respondent Demographics

Variable	Percent Response (Wave 1)	Percent Response (Wave 2)	Percent Response (Wave 3)	Percent Response (Wave 4)	Percent Response (All Waves)
Age 65+	17.1%	20.2%	0.2%	0.2%	9.50%
Age 18-44	53.4%	50.0%	63.3%	63.3%	57.4%
Income > $75K	43.6%	48.8%	46.2%	48.8%	47.0%
Female	49.9%	43.2%	48.1%	51.4%	48.0%
Bachelor's Degree	31.3%	30.9%	26.1%	25.0%	28.3%
Master's Degree or Higher	14.7%	19.0%	17.0%	20.6%	18.0%

Table 3. Location of Respondents' Next Trip

Location	Wave 1	Wave 2	Wave 3	Wave 4	All Waves
Charlotte	7.2%	8.0%	7.6%	8.3%	7.8%
Lee	8.5%	9.0%	10.3%	9.9%	9.5%
St. Lucie	9.3%	7.8%	8.8%	8.0%	8.4%
Palm Beach	18.6%	19.0%	20.1%	21.7%	19.9%
Marco & Naples	11.7%	12.6%	12.4%	10.4%	11.8%
Ten Thousand Islands	2.0%	3.3%	4.2%	3.8%	3.4%
Everglades	5.9%	5.8%	4.8%	6.0%	5.7%
Broward	9.8%	9.2%	8.8%	9.3%	9.2%
Biscayne	9.4%	8.5%	6.8%	6.7%	7.8%
Upper & FL Bay	6.0%	5.5%	6.6%	7.0%	6.3%
Middle and Lower Keys	11.6%	11.4%	9.6%	8.9%	10.3%

Table 4. Perceptions and Attitudes Towards Red Tide Events and BGA Blooms (All Waves)

Measure	Percent Agree of Strongly Agree	
	Red Tide	BGA
Florida's RT/BGA are naturally occurring.	48.5%	48.1%
Florida's RT/BGA are occurring more frequently	62.3%	66.1%
Florida's RT/BGA events are lasting longer and are more severe	60.8%	63.6%
Florida's RT/BGA are directly affected by agricultural activities.	53.8%	63.3%
Florida's RT/BGA are directly affected by urban growth	56.3%	62.3%
Any potential control methods should be used to prevent RT/BGA.	67.8%	67.2%
Control methods should be used even if the impacts of doing so are unknown.	50.1%	51.3%
There should be stricter regulations to prevent pollution discharges and runoff.	75.1%	77.3%

Table 5. Experience with Red Tide Events or Blue Green Algae Blooms

Event	Never Seen	Sometimes Seen	Often Seen	Always Seen
Red Tide	25.5%	44.6%	21.8%	8.0%
BGA	20.3%	44.0%	26.2%	9.4%

Table 6. Yes Responses with Trip Cost Increases (Outliers Removed)

Cost increase	Yes	YesCert	Total	%Yes	%YesCert
25%	578	461	691	83.65	66.71
40%	534	446	685	77.96	65.11
55%	520	420	686	75.80	61.22
70%	476	378	693	68.69	54.55
85%	439	359	695	63.17	51.65
100%	414	338	685	60.44	49.34
Total	2961	2402	4135	69.14	58.10
χ^2 [5 df]				138.09	74.67

Table 7. Yes Responses with Health Risk (Outliers Removed)

Red Tide					
Risk	Yes	YesCert	Total	%Yes	%YesCert
Very Low	578	476	776	74.48	61.34
Low	575	480	803	71.61	59.78
Medium	382	292	794	48.11	36.78
High	289	231	811	35.64	28.48
Total	1824	1479	3184	57.29	46.45
χ^2 [3 df]	343.79	261.62			
Blue Green Algae					
Risk	Yes	YesCert	Total	%Yes	%YesCert
Low	248	201	322	77.02	62.42
Medium	165	122	318	51.89	38.36
High	153	114	311	49.20	36.66
Total	566	437	951	59.52	45.95
χ^2 [2 df]	62.37	53.36			

Table 8. Recreation Demand Models: Logit with Clustered Standard Errors, Dependent Variable = YES

				Model 2					
	Model 1			Attending			Non-Attending		
	COEFF	SE	t-ratio	COEFF	SE	t-ratio	COEFF	SE	t-ratio
Constant	2.0899	0.0556	37.61	2.0895	0.0558	37.44			
COST	-0.0014	0.0001	-18.81	-0.0015	0.0001	-18.55	-0.0007	0.0002	-3.61
COST X DAY	-0.0011	0.0003	-3.30	-0.0012	0.0004	-3.05	-0.0010	0.0006	-1.52
RT Very Low risk	-1.1590	0.0871	-13.30	-1.2797	0.0898	-14.25	0.1982	0.3982	0.50
RT Low risk	-1.3094	0.0840	-15.59	-1.4348	0.0881	-16.29	-0.4116	0.2732	-1.51
RT Medium risk	-2.3121	0.0760	-30.41	-2.4281	0.0812	-29.92	-1.5399	0.2143	-7.19
RT High risk	-2.8304	0.0773	-36.64	-2.9784	0.0839	-35.51	-1.9951	0.1969	-10.14
BGA Low risk	-1.0297	0.1349	-7.63	-1.0842	0.1426	-7.60	-0.6827	0.4149	-1.65
BGA Moderate risk	-2.1700	0.1160	-18.71	-2.2652	0.1223	-18.52	-1.3999	0.3773	-3.71
BGA High risk	-2.2691	0.1164	-19.49	-2.3769	0.1251	-19.00	-1.5960	0.3336	-4.78
WAVE2	0.0565	0.0737	0.77	0.0719	0.0742	0.97			
WAVE3	0.3057	0.0735	4.16	0.3233	0.0741	4.36			
WAVE4	0.1981	0.0736	2.69	0.1994	0.0741	2.69			
χ^2		2115.9				2223.64			
McFadden's R^2		0.156				0.164			
AIC		11,466.8				11,357.0			
Cross-sections		4135				4135			
Time-periods		3				3			
Sample size		12,405				12,405			

Table 9. Recreation Demand Models: Logit with Clustered Standard Errors, Dependent Variable = YESCERT

	Model 3			Model 4					
				Attending			Non-Attending		
	COEFF	SE	t-ratio	COEFF	SE	t-ratio	COEFF	SE	t-ratio
Constant	1.6016	0.0498	32.18	1.6019	0.0499	32.13			
COST	-0.0015	0.0001	-17.85	-0.0016	0.0001	-17.69	-0.0007	0.0002	-4.02
COST X DAY	-0.0017	0.0005	-3.62	-0.0016	0.0005	-3.16	-0.0024	0.0011	-2.19
RT Very Low risk	-1.2751	0.0763	-16.72	-1.3206	0.0806	-16.39	-0.9481	0.2331	-4.07
RT Low risk	-1.3419	0.0752	-17.85	-1.4505	0.0802	-18.09	-0.6573	0.2158	-3.05
RT Medium risk	-2.2805	0.0763	-29.88	-2.3796	0.0827	-28.79	-1.6716	0.2009	-8.32
RT High risk	-2.6594	0.0801	-33.20	-2.7703	0.0876	-31.63	-2.0579	0.1958	-10.51
BGARISK1	-1.2342	0.1168	-10.57	-1.2466	0.1253	-9.95	-1.1995	0.3218	-3.73
BGARISK2	-2.2180	0.1174	-18.89	-2.2223	0.1244	-17.87	-2.2387	0.3558	-6.29
BGARISK3	-2.2849	0.1195	-19.12	-2.3697	0.1299	-18.24	-1.7998	0.3107	-5.79
WAVE2	0.1616	0.0684	2.36	0.1707	0.0687	2.48			
WAVE3	0.2058	0.0671	3.07	0.2182	0.0674	3.24			
WAVE4	0.1616	0.0674	2.40	0.1622	0.0677	2.40			
χ^2	2279.7			2340.16					
McFadden's R^2	0.147			0.151					
AIC	13,272.3			13,229.8					
Cross-sections	4135			4135					
Time-periods	3			3					
Sample size	12,405			12,405					

Table 10. Willingness to Pay Estimates: Dependent Variable = YES

				Model 2					
	Model 1			Attending			Non-Attending		
Overnight Trips	WTP	SE	t-ratio	WTP	SE	t-ratio	WTP	SE	t-ratio
Wave 1	1535.37	81.30	18.89	1435.86	77.15	18.61	3284.79	907.16	3.62
Wave 2	1570.47	82.10	19.13	1477.67	78.45	18.84	3380.45	933.75	3.62
Wave 3	1727.63	89.30	19.35	1626.16	85.10	19.11	3720.14	1027.10	3.62
Wave 4	1659.34	85.65	19.37	1552.56	81.16	19.13	3551.77	979.54	3.63
Red Tide Very Low	980.58	71.50	13.71	859.10	65.14	13.19	3822.04	1188.20	3.22
Red Tide Low	902.98	66.77	13.52	786.72	60.92	12.91	3007.12	900.48	3.34
Red Tide Medium	474.00	38.73	12.24	407.42	34.95	11.66	1691.71	518.79	3.26
Red Tide High	318.90	28.08	11.36	264.67	24.82	10.67	1266.77	390.30	3.25
Blue Green Algae Low	1108.61	95.82	11.57	1017.59	91.98	11.06	2818.93	934.79	3.02
Blue Green Algae Moderate	565.25	55.45	10.19	500.93	52.16	9.60	1969.39	680.79	2.89
Blue Green Algae High	527.75	53.80	9.81	462.90	50.65	9.14	1760.99	598.85	2.94

Table 11. Willingness to Pay Estimates: Dependent Variable = YESCERT

				Model 4					
	Model 3			Attending			Non-Attending		
Overnight Trips	WTP	SE	t-ratio	WTP	SE	t-ratio	WTP	SE	t-ratio
Wave 1	1233.84	69.22	17.83	1155.15	65.45	17.65	2546.56	633.54	4.02
Wave 2	1328.00	72.89	18.22	1248.31	69.30	18.01	2751.92	684.04	4.02
Wave 3	1354.15	73.73	18.37	1274.68	69.98	18.22	2810.05	698.47	4.02
Wave 4	1327.97	72.71	18.26	1243.63	68.65	18.12	2741.62	680.93	4.03
Red Tide Very Low	668.11	52.41	12.75	607.69	49.16	12.36	1686.09	483.78	3.49
Red Tide Low	639.85	50.46	12.68	557.80	45.99	12.13	1985.98	543.76	3.65
Red Tide Medium	323.15	28.83	11.21	279.50	26.27	10.64	1056.08	308.24	3.43
Red Tide High	236.54	22.45	10.53	201.60	20.23	9.97	794.41	236.82	3.35
Blue Green Algae Low	705.13	66.16	10.66	660.21	65.11	10.14	1498.71	476.89	3.14
Blue Green Algae Moderate	351.62	39.26	8.96	331.33	38.61	8.58	721.10	272.33	2.65
Blue Green Algae High	333.56	38.43	8.68	294.79	36.49	8.08	1003.12	339.34	2.96