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Abstract. We estimate economic benefits of avoiding reductions in drinking water quality due to sea level rise accruing to North Carolina (NC) coastal tourists. Using stated preference stated preference methods data with recent coastal visitors, we find that tourists are 2%, 8%, and 11% less likely to take an overnight trip if drinking water tastes slightly, moderately, or very salty at their chosen destination. The majority of those who decline a trip would take a trip to another NC beach without water quality issues, others would take another type of trip, with a minority opting to stay home. Willingness to pay for an overnight beach trip declines with the salty taste of drinking water. We find evidence of attribute non-attendance in the stated preference data, which impacts the regression model and willingness to pay for trips. Combining economic and hydrology models, annual aggregate welfare losses due to low drinking water quality could be as high as $401 million, $656 million and $1.02 billion in 2040, 2060 and 2080.

Key words: Attribute non-attendance, barrier-island aquifers, sea-level rise, stated preference, tourism

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Introduction

Tourism is a major component of the U.S. coastal economy, contributing about $143 billion to GDP each year (NOAA, 2023a). Sea-level rise (SLR) is an existential threat to economic viability and environmental sustainability of coastal North Carolina (Poulter 2009), with serious implications for coastal tourism due to inundation of low-lying areas, erosion of beaches and dunes, loss of buildings and public infrastructure, and intrusion of salt water into freshwater aquifers. Tidal data collected in the region by the National Oceanic and Atmospheric Administration (NOAA) indicate rates of annual SLR of 4.78 mm/y at Duck, NC (NOAA, 2023b) and 2.61 mm/y at Wilmington, NC (NOAA, 2023c). Bin et al. (2011) estimates negative impacts of SLR on property values for four coastal North Carolina counties at up to $7 billion by 2080. Losses from reduced access to shore fishing locations due to SLR are estimated at $430 million between 2005 and 2080 (Whitehead et al. 2009).

An unexplored issue in the context of SLR and coastal tourism is the impact on freshwater supplies. Availability of ample clean and safe drinking water supply can be a challenge for sustainable coastal development (Chen, Hong, and Gao 2021). Fiori and Anderson (2022) found evidence of decreasing viability of the North Carolina's barrier-island aquifers due to increasing SLR. While most towns on the North Carolina coast have public water facilities that use some form of desalinization to supply freshwater, rising sea levels are reducing the volume of freshwater in surficial aquifers in these locations, likely to increase the need for more extensive water treatment and raise costs of potable water. Also, desalinization cannot eliminate the salty taste of potable water when there are high chloride levels, as is likely to occur on some parts of the NC coast under SLR.

The effect of salty-tasting drinking water is underexplored in the context of SLR and coastal tourism. To our knowledge, only two studies have considered the willingness to pay (WTP) to avoid salinity in household water supply. Ragan, Young, and Makela (2000) use a damage function approach to estimate the costs of high salinity water on household appliances. Using the contingent valuation method (CVM) to value improvements in drinking water quality in the State of Palestine, Middle East, Alameddine, Tarhini, and El-Fadel (2018) find that existing salinity levels are determinants of WTP for improved drinking water quality. In this study we combine revealed preference (RP) and stated preference (SP) data on overnight trips to estimate the WTP to avoid SLR-induced effects on the salinity of drinking water in the coastal tourism sector. We utilize a series of dichotomous choice questions that inquire whether survey respondents would continue to take an overnight trip under various trip degradation scenarios, including higher trip costs.

Our survey design builds on the CVM approach to valuing a recreation trip. This literature began with Brown and Hammock (1973) who first asked waterfowl hunters about their total costs on all of their hunting trips over the season. They then asked hunters an open-ended question about the maximum amount the costs would be before they stopped hunting. Following a number of articles that found problems with open-ended willingness to pay data, Bishop and Heberlein (1979) introduced the dichotomous choice question. The first dichotomous choice study with a trip cost payment vehicle is Cameron and James (1987). Survey respondents who had already taken a fishing trip were asked a counterfactual question about whether they would have still taken the trip with higher trip costs. Cameron and James only analyze the stated preference data. McConnell, Weninger and Strand (1999) build on this empirical approach by analyzing both the baseline RP trip and the SP trip decisions in a panel framework.

Park, Loomis and Creel (1991) ask a dichotomous choice trip cost question and then follow-up questions about the quality of the trip, analyzing the data separately. Loomis (1997) extends this approach by analyzing the RP and SP data in a panel framework. More recently, Neher et al. (2017) ask four separate questions with changes in trip costs at different quality levels and find that the results are temporally reliable; willingness to pay estimates are similar to those estimated from the same survey from 20 years earlier. Moreover, Neher et al. (2018) find that willingness to pay estimates from dichotomous choice trip cost questions produce similar values to those from a discrete choice experiment.

Our empirical analysis first utilizes ex-post (RP) trip responses based on current conditions as a baseline. We then consider an ex-ante (planned) trip responses under current conditions, and then under alternative situations with differing quality conditions. We combine these data and analyze them in a panel framework. As an extension to the literature we control for attribute non-attendance (ANA). ANA occurs when respondents fail to consider every detail of the attributes in a valuation scenario (Lew and Whitehead 2020). The literature includes two approaches for identifying and accounting for ANA behavior in stated preference studies. The stated ANA approach employs self-reported information about ANA behavior while the inferred ANA approach relies on the use of econometric models to allow identification of ANA behavior. Inferred ANA approaches generally involve applying flexible econometric models that allow for ANA to be identified directly from patterns in the stated preference data. In this way, inferred methods do not require the use of potentially endogenous stated ANA information provided by individuals. Rather, they attempt to let the data speak for themselves about whether or not ANA behavior is present.

In the rest of the paper we describe the data, present the model, review empirical results, explore policy implications and offer conclusions. Using an inferred ANA model we find evidence of attribute non-attendance behavior in the data, suggesting significant upward bias in willingness to pay compared to the naïve (base) model. This bias has significant policy implications. We recommend that researchers routinely consider ANA, and when present, provide adjusted WTP estimates. Various approaches to account for ANA can be utilized for sensitivity analysis and robustness checks.

Data

In the spring of 2022 we surveyed 434 North Carolina (NC) residents who had taken an overnight trip to the NC coast in the previous 36 months and who did not own coastal property. The sample is from the Dynata opt-in consumer panel. We pretested the survey in 2021 with over 200 respondents. Results of the pretest helped us revise the survey and adjust the additional trip cost amounts presented to respondents. We do not include these pretest responses in the analysis sample.

Internet surveys with opt-in samples are one of the least expensive survey modes and, as a result, are widely used in the stated preference literature (Champ 2017). But these data may be lower in quality than probability-based samples. Johnston et al. (2017) assert that the highest quality surveys use probability-based sampling and employ the Dillman repeat-contacts method for quality assurance. A recent special section in the journal *Applied Economics Perspectives and Policy* (forthcoming) examined the use of opt-in survey panels. Goodrich et al. (forthcoming) find that one drawback of data from an opt-in sample is that respondents may rush through the questionnaire, paying little attention to the details of the valuation questions, which results in relatively low-quality data. Sandstrom et al. (forthcoming) compared two opt-in panels with a mixed mode mail/internet sample and found that each sample produced the expected results, but the WTP estimates in an opt-in sample were always greater than the probability-based sample. Penn et al. (forthcoming) compare a probability-based sample with a convenience sample and find differences in the determinants of willingness to pay but no differences in the magnitude of willingness to pay. Whitehead et al. (forthcoming) find that the probability-based sample data are the most likely to pass validity tests with data from in a single bounded referendum question.

This research examining opt-in panels generally supports their use but with caveats and a recognition that extra effort must be expended to develop a reliable sample. In order to increase data quality, we first asked for respondents' state of residence with a screener question before the purpose of the survey could be assessed by respondents. Non-NC residents were deleted. This was followed by an open-ended question about residents' ZIP codes. Respondents who reported ZIP codes outside the range of NC ZIP codes were deleted. We asked redundant questions to screen out additional respondents who were rushing through the questionnaire (i.e., "speeders"). We deleted 18 respondents who provided inconsistent age and/or income responses. The median time that it took respondents to complete the survey was 7 minutes.

Eighty-two percent of the original sample took an overnight trip during the previous 12 months before the interview, and 87% of the sample planned to take an overnight trip in the next

12 months. Given that our analysis involves stated preference questions about future trip conditions, we focus on the 286 respondents who planned to take an overnight beach trip to the NC coast during the next 12 months. The average age of the respondents is 46 years, and 69 percent are female (Table 1). The average household size is 2.74 people with 1.24 children. The average years of schooling is 14, and the average household income is $79 thousand. Seventy-four percent of respondents had taken an overnight trip to a NC beach in the previous 12 months (Table 2), with an overall average number of 2.8 beach trips in the past 12 months. For their most recent trip, the average number of nights stayed on overnight trips is 3, and the average party size is 4 people.

These respondents were then asked to consider their next overnight trip to the NC coast. The average number of nights that they planned to stay on their next trip is also 3, and average party size remains 4. Respondents spent an average of $749 (self-reported) on their most recent trip, and state that they plan to spend an average of $879 (self-reported forecasting) on their next overnight trip.

The first stated preference scenario includes up to two questions and considers the most recent trip (Table 3). We first ask respondents who had taken a trip in the past year to a NC beach ($n = 213$) a stated preference question for their most recent trip. We ask them to suppose that their most recent trip cost more money as a result of higher rental rates, higher prices, or some other reason. We inquire whether they would still have taken the trip if the additional trip cost was higher than the amount that they had previously spent, where the additional cost is a randomly assigned amount that ranged from $100 to $1000 in increments of $100. Sixty-five percent of the respondents state that they would have still taken the trip, with an average additional cost of $569.

In Table 4 we present the frequency tables of yes responses for each cost amount and tests for independence of the yes responses for each SP trip cost question. The percentage of yes responses to the first question (yes1) fall from 100% at $100 to 60% at $1000. The sample sizes at each cost amount are 30 or below so it is understandable that the yes responses decrease non-monotonically with the cost amount. But, consistent with demand theory, a chi-square test indicates that the percentage of respondents who state that they would have still taken the trip is non-constant over the additional cost range.

For those respondents that affirmed they would still have taken the trip at a higher cost we ask a follow-up question with a randomly assigned increased cost amount that ranges from $1100 to $1500 in increments of $100. Forty-nine percent of these respondents state that they would have still taken the trip, with an average additional cost of $1306 (Table 3). At these higher costs, the percentage of respondents who state that they would have still taken the trip does not vary as the cost amount increases (yes1f, Table 4).

The second stated preference scenario is similar to the first but focuses on the next planned overnight trip to the NC coast ($n = 286$). We ask respondents if they would still take the trip if the cost was higher than the amount that they think they will spend, assuming costs are not higher at other potential substitute beach sites. Again, the added cost is a randomly assigned amount that ranged from $100 to $1000 in increments of $100. The additional specified cost was $560, on average, and fifty-seven percent of the respondents stated that they would still take the trip (Table 3). The percentage of respondents who state that they would still take the trip falls (yes2) as the cost increases, again, consistent with demand theory (Table 4).

If the respondent states that they would still have taken the trip we pose the question again with a randomly assigned cost increase that ranges from $1100 to $1500 in increments of $100. Fifty-two percent of these respondents state that they would still take the trip, with an average additional cost of $1288 (Table 3). As in the first scenario, the percentage of respondents who state that they would still take the trip (yes2f) does not vary as the cost amount increases at these higher amounts (Table 4).

The questionnaire then turned to the issue of sea-level rise. Respondents were told: "The National Oceanic and Atmospheric Administration (NOAA) estimates that sea levels along the North Carolina coast have been rising at a rate of about 1/8 inch to almost a 1/4 inch per year over the last several decades. At that rate, sea levels along the entire North Carolina coast will be more than 1 inch to 2 inches higher in the next 8 years." Then respondents were asked if they were previously aware that sea levels have been rising along the NC coast. Fifty-seven percent of respondents indicated that they were aware of SLR.

Respondents were then told about the problem of saltwater intrusion: "This increase in sea-level poses several issues to coastal communities. One of these issues is drinking water quality. Saltwater can more easily mix with freshwater sources making water undrinkable. This is known as saltwater intrusion. Most of the North Carolina coastal communities are using a desalination treatment process. In this situation, continued saltwater intrusion will increase treatment costs and may make the water taste salty." In response, 37 percent of respondents indicated that they were very concerned about drinking water quality at NC beaches in the future.

The hypothetical decrease in drinking water quality at the location of the respondent's next beach trip is then described, as follows: "Now try to imagine a situation where [chosen NC beach] is dealing with saltwater intrusion and drinking water quality in 2022. In this situation the water from the tap is treated by desalination. It is safe to drink and fine for bathing, washing dishes and washing clothes. But, the water would taste salty. The potential salty taste can be described on the following scale:

1. Slightly intense (barely noticeable compared to your usual tap water)
2. Moderately intense (somewhat noticeable)
3. Very intense (definitely noticeable)

An ‘extremely intense’ salty taste is like when you accidentally swallow ocean water while swimming. The tap water would never be this salty.” Respondents were then asked how the tap water from their home tastes, with most (56%) stating that it “tastes fine, no complaints”. Only 4 percent stated that their home tap water tasted salty.

Respondents were then given details about a third stated preference scenario. They were asked what they would do if there were drinking water problems at their chosen NC beach. Then we explained several options: (i) respondents could take the trip because they do not think it would be an issue, or could find another source for drinking water; (ii) they could decide to take a trip to another NC beach; or (iii) do something else entirely. Respondents were told that the water quality problems, in this scenario, were isolated to their chosen NC beach and, thus, drinking water at all other NC beaches did not have a salty taste. In addition, respondents were instructed that they could cancel or change their reservations at no cost, and other costs associated with the trip would not change. Respondents were not asked to assume that averting expenditures (e.g., purchases of bottled water) would not change. The added cost variable may suffer from measurement error that is increasing in the extent that respondents did consider averting expenditures. As an internal quality check, we inquired about attentiveness to the survey scenario/instructions. Seventy-five percent of respondents stated that they read the instructions very closely, 23% said they read them somewhat closely and 2% percent said that they did not read the instructions closely.

Respondents are first presented with one of two drinking water quality scenarios – slightly salty or moderately salty tasting water – and asked if they would still take their planned beach trip. Eighty-seven percent of respondents would still take their planned trip in this scenario. We follow-up with those respondents who would still take the trip to assess whether they would take their planned trip if the drinking water tasted very salty; seventy-nine percent of 248 respondents would still take the trip. Finally, these remaining respondents are asked if they would still take the trip if the cost increased with the very salty taste. The cost increase was a randomly assigned amount from $100 to $1500 in increments of $100. Fifty-percent of these remaining respondents would still take the trip if the average cost increase was $724 (yes3, Table 3). The percentage of respondents who state that they would still take the trip falls as the cost amount increases (Table 4).

After the last trip question in each of the three scenarios, we inquire about substitution patterns for those respondents who said that they would no longer take their chosen trip ($n = 187$). Following the third scenario, 42% of the respondents said that they would go to another NC beach; 33% said that they would take a trip somewhere other than a NC beach; 24% said that they would stay home, and 2% said that they would do another activity entirely. Twenty-one percent of the respondents who stated that they would still go to their chosen beach if the water tasted very salty and the trip cost more ($n = 99$) indicated that they did not think the drinking water problem would be an issue for them. Seventy-eight percent said that they would bring drinking water from home, buy drinking water at the beach, or do both. Those who stated that they would buy drinking water were asked how much they think they would spend on bottled water during the trip. The mean averting expenditures for hauling or buying water is $36 per trip (n= 78).

Similar to McConnell, Weninger, and Strand (1990) and Loomis (1997), we combine ("stack") the RP and SP trips under baseline conditions with SP trips with posited cost increases and increased drinking water salinity. The data are an unbalanced, quasi-panel with three trip scenarios (RP trips with cost increases; SP trips with cost increases; and SP trips with cost increases and increases in drinking water salinity) and up to three trip responses in each scenario (Table 3). The quasi-panel data consist of 2031 observations for the 286 respondents.

Model

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. 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 $v(q', y-p) \geq v(y)$, where $q > q' > \bar{q}$, and $\bar{q}$ is the reservation quality for a given price, $x(p, \bar{q}) = 0$. When faced with a cost increase and a degradation in trip quality, the consumer will continue to take the trip if $v(q', y-p-c) \geq v(y)$.

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 (decreasing in price), $v_j(q, y) + \varepsilon_j$, 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, 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 questions in each scenario.

Estimation of the parameters is achieved by stacking the change in indirect utility functions considering the $t \leq 9$ observations (choice occasions) for each respondent, $\Delta v_{\mathrm{it}} = \tilde{\beta} +$

$\beta_y c_{\mathrm{it}} + \beta_q q_{it} + \tilde{\varepsilon}_{\mathrm{it}}$. Assuming ε are drawn from a joint logistic distribution, the probability that individual i will choose to take the trip in occassion t is

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

The equality-constrained latent class (ECLC) model (Scarpa et al. 2009) assumes individuals fall into one of several discrete and latent classes, where each latent class is defined by which attributes are attended to. The model assumes that across classes, utility difference parameters for the attributes that are attended to are equivalent. This contrasts with standard latent class logit models that allow the preference parameters to differ across classes. The ECLC model is referred to as an inferred ANA model since it gleans ANA behavior directly from the likelihood function and patterns in the choice data, without the aid of stated ANA information from the respondents. A single parameter vector is estimated in the ECLC model, and each latent class is differentiated by which parameters are constrained to be zero and assumed to be ignored. The probability of observing the individual *i* taking the trip at choice occasion *t* is:

(2) $$\pi(x_{\mathrm{it}} = 1) = \sum_{k=1}^{K} \left[\left(\frac{\exp{(\theta_l)}}{\sum_{k=1}^{K} \exp{(\theta_k)}} \right) \times \frac{1}{1+exp(-\Delta v_{it})} \right]$$

The left-most term in the right-hand side of the equation is the probability of membership in latent class l, where θ_k is a class-specific constant parameter to be estimated, K is the number of classes and $\sum_{k=1}^{K} \frac{\exp{(\theta_l)}}{\sum_{k=1}^{K} \exp{(\theta_k)}} = 1$.

In general, if the estimated utility model is $\Delta v = \tilde{\beta} - \beta_q q - \beta_y c$, where q is a quality vector, $q = S, M, V$, then the willingness to pay (WTP) for an overnight beach trip without degraded quality is $WTP = -\tilde{\beta}/\beta_c$. This is the mean (and median) welfare 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). Another welfare estimate involves truncating the portion of the logit curve with negative WTP and including the tail of the logit curve distribution in the calculation: $WTP' = \frac{-1}{\beta_c} \ln\left(1 + exp\left(\tilde{\beta}\right)\right)$ (Hanemann 1989). Considering this truncation, $WTP' > WTP$ and the difference will be decreasing in the constant of the logit model. However, these differences are slight in our models. Nevertheless, we choose to present the truncated mean WTP estimate since it provides a more conservative estimate of some of the differences in WTP due to changes in drinking water quality.

Results

We first estimate a base case binary logit model with clustered standard errors at the individual level: $\Pr(x_{it} = 1) = f(C_{it}, S_{it}, M_{it}, V_{it})$, where x = 1 if the respondent would take the trip, C is the added trip cost, $S = 1$ if the salty taste is "slightly intense", $M = 1$ if the salty taste is "moderately intense" and $V = 1$ if the salty taste is "very intense". The baseline for the taste variables is no salty taste ($S = M = V = 0$), which reflects the drinking water quality at the time of the survey. This model is labeled as the naïve model because it assumes no ANA behavior (column 1, Table 5). The coefficient on the added trip cost variable is negative and statistically significant. The coefficients on the quality variables are negative and statistically significant. The quality coefficients are increasing (in absolute value) as salty taste becomes more intense, but the differences in the coefficients on the moderately salty and very salty variables are not statistically different ($\chi^2[1\ df] = 0.68$).

We then estimate two binary logit ANA models (Table 5). The first ANA model (column 2, Table 5) is suggested by Malone and Lusk (2018) and is labeled M&L. For this approach a 2-dimensional latent class logit model is estimated with a full preservation class (the attribute coefficients are estimated) and a full non-attendance class (all attribute coefficients are restricted to zero). The probability of a respondent being in the second class can be conceptualized as an estimate of likelihood that the respondent did not pay attention to the scenario attributes (in this case, cost and the saltiness of their drinking water).

The M&L model is statistically superior to the naïve model with a lower AIC and higher model χ^2 statistics. The average estimate of non-attendance in the M&L model is 31%, suggesting that almost a third of respondents did not pay attention to scenario attributes. The coefficient on the added trip cost variable is negative and statistically significant and 133% larger in absolute value than the same coefficient in the naïve model. Thus, controlling for ANA significantly increases the estimate of marginal utility of income and sensitivity to cost changes, suggesting significant bias in the naïve model. The coefficients on the quality variables are negative, statistically significant and increasing (in absolute value) as the posited salty taste increases in intensity. The coefficients on the slightly, moderate and very salty tasting water variables are 313%, 207% and 173% larger in absolute value than the coefficients in the naïve model. Similar to the naïve model, the differences in the coefficients on the moderately salty and very salty variables are not statistically different ($\chi^2[1\ df] = 0.19$). The differences in the magnitudes of the coefficient estimates are as expected if ANA behavior is present. ANA suggests that the cost and quality coefficients will be zero in the utility difference model. Ignoring ANA behavior biases the coefficient estimates towards zero. Note that it is difficult to disentangle ANA behavior from behavior associated with zero marginal utility parameters with the ECLC model. This is likely only a problem with the quality parameters because all households presumably do have a positive marginal utility of income.

The second ANA model is the ECLC model (Scarpa et al. 2009). The ECLC model assumes that individuals fall into one of several latent classes, where each is defined by which attributes are attended to, or not. Coefficients for the attributes that are attended to are assumed to be the same across all classes. The ECLC model is statistically superior to the naïve and M&L models with a lower AIC and higher model χ^2 statistics (column 3, Table 5). We find that the probability that a survey respondent fully pays attention to each of the attributes is 40%. The probability that a survey respondent pays attention to none of the attributes is 24% (which is notably lower compared to the 31% estimated under the more restrictive M&L model). Eight percent of the sample is estimated to ignore only the cost attribute, and 29% of the sample ignores only the very salty taste attribute. In preliminary models we found no evidence of non-attendance to the slightly or moderately salty taste attributes or any combination of the cost and quality attributes and drop these classes in the model presented in Table 5.

The coefficient on the cost variable is negative and statistically significant. The cost coefficient in the naïve model is 37.5% of that in the ECLC model. The coefficients on the quality variables are negative, statistically significant, and increasing (in absolute value) as the posited saltiness of the water increases in intensity. In contrast to the naïve and M&L models, when ANA behavior is accounted for in the ECLC model the coefficients on the moderately and very salty taste variables are statistically different ($\chi^2[1\ df] = 6.05$). The quality coefficients are increasing in magnitude from the naïve model to the M&L model to the ECLC model. The coefficients on the slightly, moderate and very salty tasting water variables are 42%, 21% and 74% larger in absolute value than the same coefficients in the M&L model. These results are consistent with attribute non-attendance. Not accounting for ANA in the naïve model underestimates the effect of cost and quality attributes. Allowing for zero parameters for those subjects that appear most likely to have ignored particular attributes (ANA models) increases the estimated effect of cost and quality on choice probabilities. In our application, the ECLC model appears to do a better job of tailoring ANA to latent classes within the dataset.

Willingness to Pay

Holding water quality at the current baseline of no saltiness, if β_y is biased towards zero in a naïve model where the researcher ignores ANA behavior, as found in both of the estimated ANA models, then the base case WTP estimate will be biased upwards in the naïve model. We find that the WTP for a trip is biased upwards in the naïve model. The WTP for an overnight trip is \$1173 in the naïve model, \$594 in the M&L model and \$573 in the ECLC model. This upward bias in the naïve model can be observed in the logistic regression curves (Figure 1). The naïve model has a relatively flat curve with a fat tail that reaches only a 31% probability that the respondent would not take the trip with the highest trip cost increase included in the stated preference question. In contrast, the estimated probability at the highest cost amount is 1% in the M&L model and 0.5% in the ECLC model. In two-tailed tests, the M&L and ECLC WTP estimates are statistically different from the base case WTP estimate at the $p = 0.068$ ($t = 1.83$)

and $p = 0.058$ ($t = 1.90$) levels, respectively. The base case WTP estimates for the two ANA models are not statistically different ($p = 0.57$).

The willingness to pay for a trip with a quality degradation is $WTP_q' = \frac{-1}{\beta_c}\ln\left(1 + \exp\left(\tilde{\beta} + \beta_q\right)\right)$, 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. If β_q is biased towards zero as the researcher ignores ANA behavior with the naïve model, then the impact is to bias the WTP_q estimate downwards. Whether the overall difference is biased upwards or downwards depends on the relative effects of the bias in the numerator and denominator.

The patterns that we find in the logit models translate to differences in welfare estimates for quality. The WTP estimates for a trip with slightly salty tasting drinking water are \$1057 in the naïve model, \$438 in the M&L model and \$376 in the ECLC model (Table 6). The M&L and ECLC WTP estimates are statistically different from the base case WTP estimate at the $p = 0.053$ ($t = 1.95$) and $p = 0.032$ ($t = 2.15$) levels. The WTP estimates for the two ANA models are not statistically different ($p = 0.42$).

The WTP estimates for a trip with moderately salty tasting drinking water are \$870 in the naïve model, \$325 in the M&L model and \$284 in the ECLC model. The M&L and ECLC WTP estimates are statistically different from the base case WTP estimate at the $p = 0.05$ ($t = 1.94$) and $p = 0.038$ ($t = 2.09$) levels. The WTP estimates for the two ANA models are again not statistically different ($p = 0.51$).

We find the biggest differences in welfare estimates for the most extreme scenario. The WTP estimates for a trip with very salty tasting drinking water are \$784 in the naïve model, \$304 in the M&L model, and \$157 in the ECLC model. The M&L and ECLC WTP estimates are statistically different from the base case WTP estimate at the $p = 0.099$ ($t = 1.66$) and $p = 0.032$ ($t = 2.15$) levels. The WTP estimates for the two ANA models are statistically different at the $p = 0.003$ level ($t = 3.02$). The difference in this last pair of estimates is driven by the ANA behavior detected in the very salty taste scenario by the ECLC model.

The change in WTP for a trip with a slightly salty drinking water taste (relative to the base case WTP) is \$115 in the naïve model, \$156 in the M&L model, and \$197 in the ECLC model (Table 6). The change in WTP for a trip with a moderately salty drinking water taste is \$303 in the naïve model, \$268 in the M&L model, and \$288 in the ECLC model. None of these differences in WTP estimated across the models are statistically significant from each other. The change in WTP for a trip with a very salty drinking water taste is \$388 in the naïve model, \$289 in the M&L model, and \$415 in the ECLC model. Only the difference in the change in WTP estimates between the M&L and ECLC models are statistically different. This is at the $p = 0.017$ ($t = 2.40$) level in a two-tailed test.

In Figure 2 we illustrate the logistic regression curves for the naïve and ECLC models at different levels of water quality. The naïve model exhibits relatively small decreases in demand. The decrease in the probability of a trip averages 5.2%, 14.5% and 19.1% over the range of cost increases for trip demand with slightly, moderately, and very salty tastes. In contrast, the average decrease in the probability of a trip in the ECLC model is 13.0%, 19.1% and 27.6% for slightly, moderately, and very salty tasting drinking water.

We investigated the sensitivity of our results to a number of sample selection decisions. When separately dropped the ex-post scenario data (t =1, 2, 3) and the follow-up WTP question data (time = 3, 6). We find that the magnitudes of the non-attendance probabilities vary but the pattern is similar to what is presented above. We also find that WTP magnitudes differ slightly but the pattern of differences across models is the same.

Policy Implications

Fiori and Anderson (2022) studied the effects of SLR on the primary source of freshwater to the barrier-island aquifers of North Carolina. Using an analytical model based on low groundwater gradients, limited room for upward expansion of the water table, and applying SLR projections from the Intergovernmental Panel on Climate Change (IPCC, 2014) and NOAA (NOAA, 2020), the authors found decreasing viability of the state's barrier-island aquifers with increasing SLR. Aquifer risk maps based on model output from this research show that most of the state's coastal aquifers are under threat from SLR over the next 60 years, but also that narrower islands and/or high-permeability barrier-island aquifers in areas of faster SLR, such as along the northern North Carolina coast, are the most vulnerable.

We use the model in Fiori and Anderson (2022) to develop estimates of five levels of drinking water quality for the years 2040, 2060 and 2080. The calculations for salt concentrations in the aquifer are based on island width, aquifer thickness, and hydraulic conductivity, and produce estimates of the position of the toe of the saltwater wedge under SLR scenarios (see Fiori and Anderson, 2022, for more detailed information on the model). We then take the model output data and calculate average aquifer salinities based on the ratio of the area of the saltwater wedge to the total area of the aquifer. This gives a salinity per unit length of aquifer. There are several important caveats regarding the calculated salinity values: the salinity calculated is based on the area ratio and does not include potential saltwater intrusion induced by pumping, nor does it include the effects of tidal oscillations, wave action, or extreme storm events, including overwash.

We consider 31 beaches in North Carolina for which survey respondents reported the destination of their next beach trip in 2022 (the trip frequencies and results of the salinity calculations for each beach can be found in the Appendix Tables). We estimate that in 2040, 45% of these beaches will continue to experience freshwater in their aquifers, 23% will have slightly salty tasting water, 16% will experience moderately salty tasting water, 3% will suffer very salty tasting water, and 13% of the beaches will be left with no freshwater aquifer (Table 7). In 2060, the number of beaches with no salty taste falls to 39%, 32% have (slightly, moderately, or very) salty tasting water, and the number without an aquifer rises to 32%. Beaches with no salty tasting water falls to 6%, 39% have salty tasting water to some degree, and 55% have no aquifer in 2080.

We next assign each beach its corresponding WTP for a beach trip from Table 7, based on baseline salinity levels (not salty), and then weight the WTP per beach by its visitation frequency (*vf*): $\overline{WTP} = \sum_{j=1}^{J} vf_j \, WTP_q$, where $\sum_{j=1}^{J} vf_j = 1$ over $j = 1, \dots, 31$ beaches. If the beach is predicted to lose its freshwater aquifer we assign it a willingness to pay equal to zero. We then repeat this exercise based on the beach-specific salinity levels projected for 2040, 2060, and 2080. In other words, in this exercise we estimate the welfare losses that could occur if there was an instantaneous decrease in drinking water quality that corresponds to the projected levels for future years. Considering the naïve model, the weighted mean WTP for an overnight beach trip is $995 for the predicted salinity levels in 2040, $756 for the 2060 levels and $537 for the 2080 levels. These represent welfare losses of 85%, 64% and 46%, respectively, relative to the

2022 no saltiness baseline. The weighted WTP estimates in the ECLC model are $430, $340, and $210 for the projected salinity levels for 2040, 2060 and 2080. The welfare losses that are estimated to occur if these higher salinity levels are experienced today correspond to a 75%, 59% and 37% loss, respectively.

According to the State of NC's tourism office (Visit North Carolina, 2023), there were 9.8 million overnight trips taken to the NC coast in 2019 (pre-covid), ninety-five percent of which are for leisure. Among those overnight vacation trips, 51% originate from NC, of which 60% are for the primary purpose of visiting the beach. Therefore, we aggregate our results over an estimated 2.86 million overnight beach trips taken by NC residents. We use frequency estimates of trip locations from the survey to create an estimate of the welfare loss of SLR-induced drinking water quality degradation relative to a welfare baseline of $3.2 billion and $1.6 billion in the naïve and ECLC models. Considering the naïve model, we estimate that the welfare loss will be 5% in 2040, 15% in 2060 and 22% in 2080 of the $3.2 billion base case welfare (Table 8). Aggregate losses are $490 million, $1.15 billion and $1.75 billion in 2040, 2060 and 2080. With the ECLC model, the welfare loss estimate is 25% in 2040, 34% in 2060 and 42% in 2080 of the $1.6 billion base case. Aggregate losses are $401 million, $656 million and $1.02 billion in 2040, 2060 and 2080, respectively. While the welfare loss relative to the baseline is larger in the ECLC model, the magnitude of the losses are larger in the naïve model due to the larger baseline welfare estimate.

The welfare exercise above presumes an instantaneous change where current salinity levels in drinking water increase to the levels that are projected for 2040, 2060, and 2080. Obviously, this increase in drinking water salinity will be more gradual, and it is possible that drinking water technologies and regulations curb such degradation. A more optimistic scenario would involve an assumption of an improvement in drinking water technology that would leave drinking water quality at levels no worse than slightly salty. The weighted WTP associated with this assumption is $1118 in 2040, $1114 in 2060 and $1074 in 2080 in the naïve model, which corresponds to welfare losses of 4.7%, 5.1%, and 8%. Relative to the 2020 baseline salinity levels, aggregate losses are $152 million, $163 million and $271 million in 2040, 2060 and 2080, respectively. The weighted WTP estimates in the ECLC model are $478, $471, and $405 for the salinity levels projected for 2040, 2060 and 2080. The welfare losses relative to the 2022 baseline are 16%, 18% and 29%. Aggregate losses are $266 million under the 2040 salinity levels scenario, $285 million for 2060 scenario, and $474 million for 2080.

In the more optimistic case, the naïve model understates the welfare losses. This different outcome is because of the higher weight placed on the welfare loss associated with a slightly salty taste in the ECLC model ($197) relative to the naïve model where the difference is smaller ($115). Of course, the cost of the new technology should be less than the difference between the pessimistic and optimistic measures of welfare for its adoption to make economic sense. The cost of any improvements in drinking water technology is unknown and not part of our welfare loss calculations.

Conclusions

In this paper we find that SLR effects on drinking water taste potentially have significant implications for consumer welfare and the tourist economy in North Carolina. Considering the preferred ECLC model, we estimate that North Carolina residents are less likely to take an overnight trip to NC beach towns if drinking water has a slightly (13%), moderately (19%), or very intense (28%) salty taste. These trip decreases translate into an annual loss in welfare of $401 million, $656 million, and $1.02 billion in pessimistic scenarios where salinity levels in the drinking water increase to levels forecasted for in 2040, 2060 and 2080, respectively, due to SLR (with no new desalination technology and drinking water standards that allow higher salt concentrations).

We have assessed the effect of attribute non-attendance in stated preference models of recreational trip-taking. Using latent class models we find a significant amount of inferred attribute non-attendance behavior in the data with only 40% to 69% of the sample fully engaged. The ANA behavior reduces the baseline willingness to pay estimates by 50%. This is due to the biased cost coefficient in the naïve model that does not consider ANA behavior. This bias could reflect well-known problems in stated preference data such as hypothetical bias or fat tails (Penn and Hu. 2023, Parsons and Myers 2016). We also find biased coefficients in the drinking water quality attributes. This bias is related to the problem of insensitivity to scope (Giguere et al. 2020). Our results suggest that the influence of these stated preference behavioral anomalies on the results can be mitigated with ANA models.

Accounting for ANA behavior significantly reduces aggregate losses in the pessimistic technology scenario. The annual welfare loss using the ECLC model is 34% lower for the 2040 salinity levels, 57% lower for the 2060 levels, and 54% lower for the 2080 levels. These aggregate results do not account for all of the potential losses since we did not consider day trips and hold the number of overnight trips constant, only NC residents are included and these account for only 51% of all overnight trips to NC beaches, and we do not consider economic surplus losses on the producer side.

These results lead to at least two directions for future research with these data and other applications. First, we restricted our attention to the ECLC model. There are a large number of stated and inferred ANA models in the literature. Studies that have a focus on providing estimates for policy analysis should consider a broader range of models to determine the robustness of estimates from a single ANA approach. Second, our data is from an opt-in panel. Future research should compare attribute non-attendance models with opt-in and probability-based samples to determine if data quality is a factor in studies like this. Finally, attention paid to ANA in SP studies is not widespread, despite a long history of evidence of ANA in the literature. Researchers should routinely consider the presence of ANA behavior in their data and, at the very least, estimate ANA models as a robustness check on standard models.

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Open Research

The questionnaire, data in MS Excel, SAS and Limdep (www.limdep.com) formats, and SAS and Limdep program files are available at the OSF webpage: https://osf.io/xrvdn.

References

Alameddine, I., R. Tarhini, and Mutasem El-Fadel. "Household economic burden from seawater intrusion in coastal urban areas." Water International 43, no. 2 (2018): 217-236.

Bin, Okmyung, Ben Poulter, Christopher F. Dumas, and John C. Whitehead. "Measuring the impact of sea-level rise on coastal real estate: A hedonic property model approach." Journal of Regional Science 51, no. 4 (2011): 751-767.

Bishop, Richard C., and Thomas A. Heberlein. "Measuring values of extramarket goods: Are indirect measures biased?" American Journal of Agricultural Economics 61, no. 5 (1979): 926-930.

Brown, Gardner Mallard, and Judd Hammack. "Dynamic economic management of migratory waterfowl." Review of Economics and Statistics (1973): 73-82.

Cameron, Trudy Ann, and Michelle D. James. "Efficient estimation methods for" closed-ended" contingent valuation surveys." The Review of Economics and Statistics (1987): 269-276.

Champ, P. A. 2017. “Collecting survey data for nonmarket valuation.” In A Primer on Nonmarket Valuation, 2nd Edition, edited by Patricia Champ, Kevin Boyle, and Thomas Brown, 59-98, Springer, Netherlands.

Fiori N, WP Anderson Jr (2022) The impact of sea-level rise on saltwater intrusion for barrier-island aquifers in North Carolina, Continental Shelf Research 244, doi:10.1016/j.csr.2022.104789.

Giguere, C., C. Moore, and J. C. Whitehead. 2020. “Valuing Hemlock Woolly Adelgid Control in Public Forests: Scope Effects with Attribute Nonattendance.” Land Economics 96(1): 25-42.

Goodrich, B. K., M. Fenton, J. Penn, J. Bovay, T. Mountain. 2023. "Battling Bots: Experiences and Strategies to Mitigate Fraudulent Responses in Online Surveys." Forthcoming, Applied Economic Perspectives & Policy.

Guignet, Dennis, Ash Morgan, Craig Landry, John Whitehead, and William Anderson, “Sea-level Rise, Groundwater Quality, and the Impacts on Coastal Homeowners,” paper presented at the NAREA Annual Meeting, June 2023.

Hanemann, W. M. 1984. “Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses.” American Journal of Agricultural Economics 66(3): 332-341.

Johnston, R. J., K. J. Boyle, W. Adamowicz, J. Bennett, R. Brouwer, T. A. Cameron, W. M. Hanemann, N. Hanley, M. Ryan, R. Scarpa, and R. Tourangeau, R. 2017. “Contemporary

Guidance for Stated Preference Studies.” Journal of the Association of Environmental and Resource Economists 4(2): 319-405.

Lew, Daniel K., and John C. Whitehead. "Attribute non-attendance as an information processing strategy in stated preference choice experiments: Origins, current practices, and future directions." Marine Resource Economics 35, no. 3 (2020): 285-317.

Loomis, John B. "Panel estimators to combine revealed and stated preference dichotomous choice data." Journal of Agricultural and Resource Economics (1997): 233-245.

IPCC, 2014. In: Pachauri, R.K., Meyer, L.A. (Eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Core Writing Team. IPCC, Geneva, Switzerland, 151 p.

McConnell, Kenneth E., Quinn Weninger, and Ivar E. Strand, Joint Estimation of Contingent Valuation and Truncated Recreational Demands, Chapter 7 in Valuing Recreation and the Environment, edited by Joseph A. Herriges and Catherine L. Kling, Edward Elgar, 1999.

Michael HA, CJ Russoniello, LA Byron (2013) Global assessment of vulnerability to sea-level rise in topography-limited and recharge-limited coastal groundwater systems, Water Resources Research 49, 2228–2240, doi:10.1002/wrcr.20213.

Neher, Chris, John Duffield, Lucas Bair, David Patterson, and Katherine Neher. "Testing the limits of temporal stability: willingness to pay values among Grand Canyon whitewater boaters across decades." Water Resources Research 53, no. 12 (2017): 10108-10120.

Neher, Christopher, Lucas Bair, John Duffield, David Patterson, and Katherine Neher. "Convergent validity between willingness to pay elicitation methods: an application to Grand Canyon whitewater boaters." Journal of Environmental Planning and Management (2018): 1-15.

NOAA Sea Level Rise Viewer, 2020 from. https://coast.noaa.gov/slr/#/layer/sce/0/-8546923.36190655/4165915.9764845944/9/satellite/19/0.8/2020/inter/midAccretion .

NOAA (2023a), Office for Coastal Management, Fast Facts: Tourism and Recreation, https://coast.noaa.gov/states/fast-facts/tourism-and-recreation.html, accessed on 6 October, 2023.

NOAA (2023b) National Oceanic and Atmospheric Administration Relative Sea Level Trend, 8651370 Duck, North Carolina, accessed on 20 February, 2023.

NOAA (2023c) National Oceanic and Atmospheric Administration Relative Sea Level Trend, 8658120 Wilmington, North Carolina, accessed on 20 February, 2023.

Park, Timothy, John B. Loomis, and Michael Creel. "Confidence intervals for evaluating benefits estimates from dichotomous choice contingent valuation studies." Land economics 67, no. 1 (1991): 64-73.

Parsons, G. R., and K. Myers. 2016. “Fat Tails and Truncated Bids in Contingent Valuation: An Application to an Endangered Shorebird Species.” Ecological Economics 129: 210-219.

Penn, J. M., D. R. Petrolia, J. M. Fannin. 2023. "Hypothetical Bias Mitigation in Representative and Convenience Samples." Forthcoming, Applied Economic Perspectives & Policy.

Poulter, Benjamin, Rebecca L. Feldman, Mark M. Brinson, Benjamin P. Horton, Michael K. Orbach, Samuel H. Pearsall, Enrique Reyes, Stanley R. Riggs, and John C. Whitehead. "Sea-level rise research and dialogue in North Carolina: Creating windows for policy change." Ocean & Coastal Management 52, no. 3-4 (2009): 147-153.

Ragan, Guy E., Robert A. Young, and Carole J. Makela. "New evidence on the economic benefits of controlling salinity in domestic water supplies." Water Resources Research 36, no. 4 (2000): 1087-1095.

Sandstrom, K., F. Lupi, H. Kim, and J. A. Herriges. 2023. "Comparing Water Quality Valuation Across Probability and Non-Probability Samples." Forthcoming, Applied Economic Perspectives and Policy.

Scarpa, Riccardo, Timothy J. Gilbride, Danny Campbell, and David A. Hensher. "Modelling attribute non-attendance in choice experiments for rural landscape valuation." European review of agricultural economics 36, no. 2 (2009): 151-174.

Visit North Carolina, (2023), https://partners.visitnc.com/research, accessed on 6 October 2023.

Whitehead, John. 2023. “Sea Level Rise and WTP for Drinking Water Quality.” OSF. October 6. osf.io/xrvdn.

Whitehead, John C., Ben Poulter, Christopher F. Dumas, and Okmyung Bin. "Measuring the economic effects of sea level rise on shore fishing." Mitigation and Adaptation Strategies for Global Change 14 (2009): 777-792.

Figure 1. Logistic regression curves for three models and baseline water quality

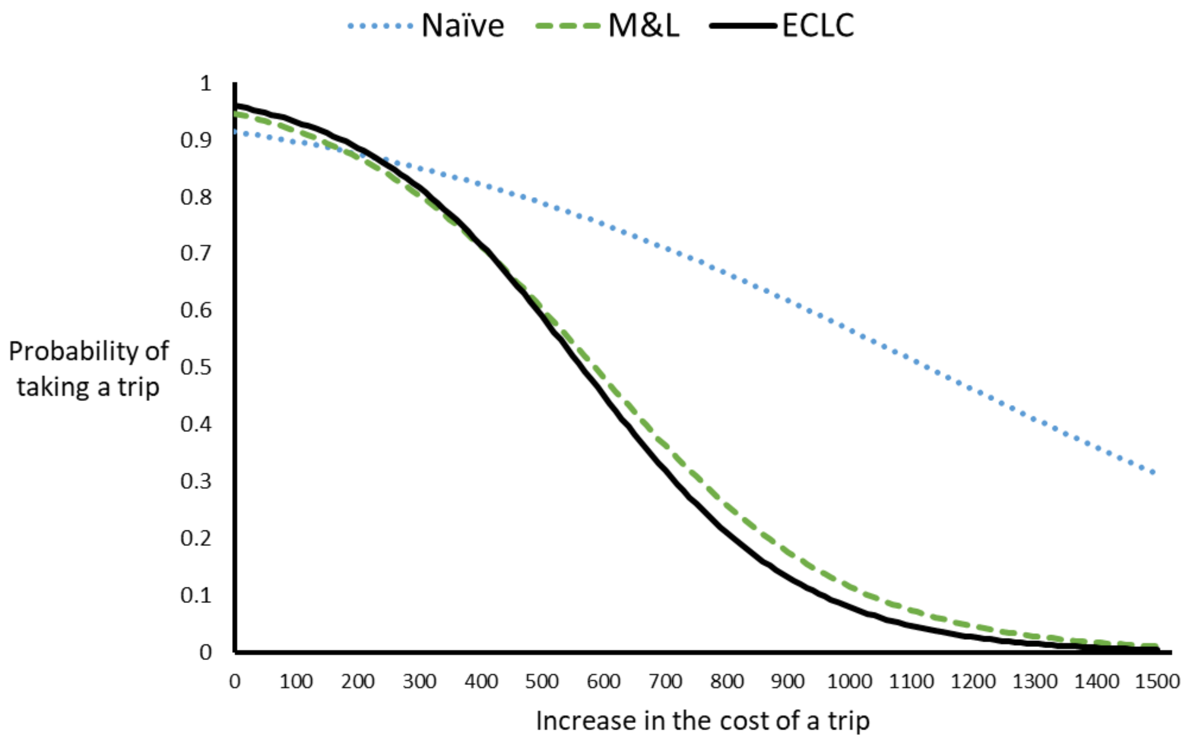

Figure 2. Logistic regression curves for the Naïve and ECLC models with different levels of water quality

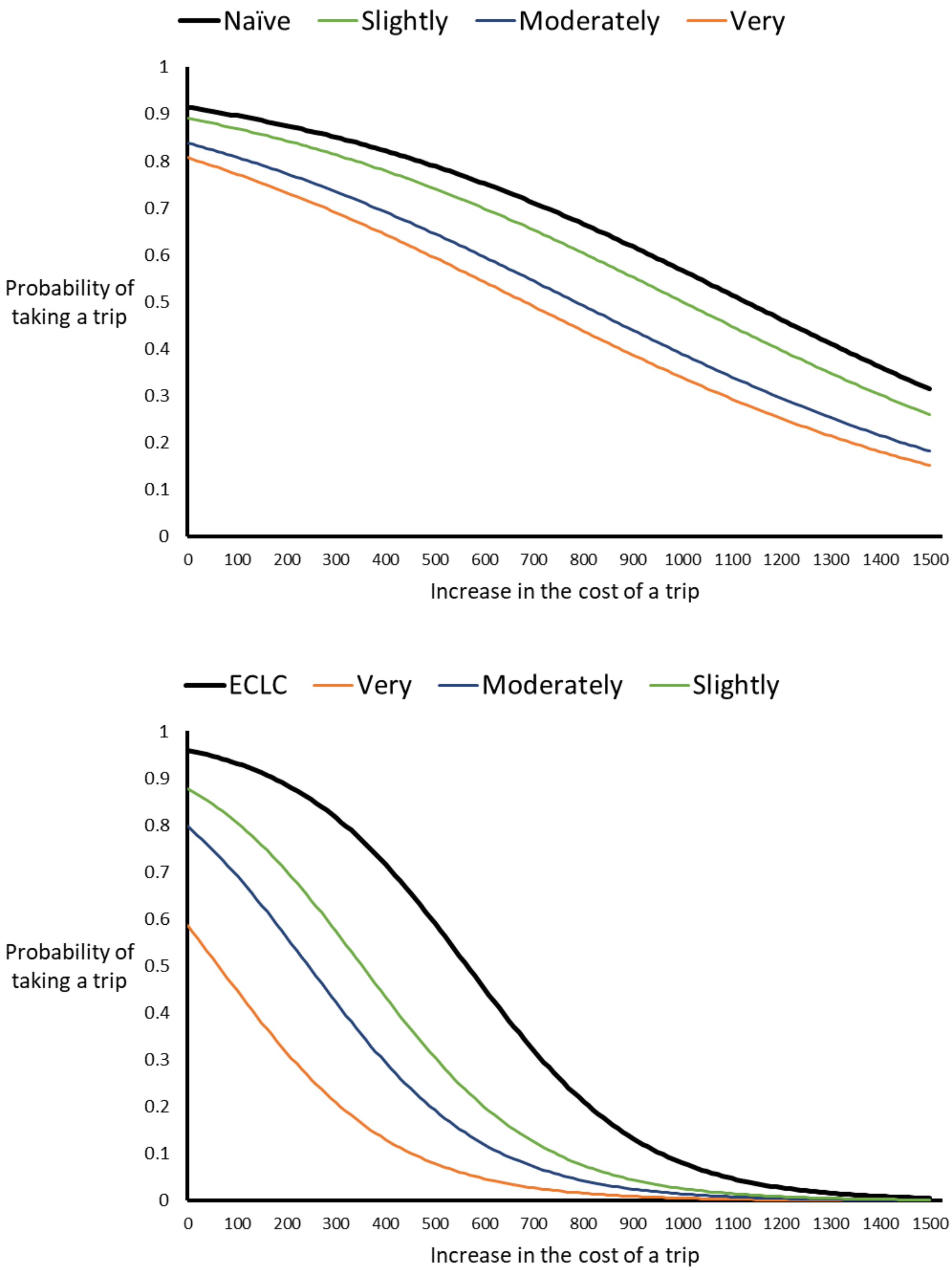

Table 1. Sample Demographics

Variable	Label	Mean	Std Dev
Age	age in years	46.38	15.43
Female	1 if female, 0 otherwise	0.69	0.47
House	household size	2.74	1.20
Children	number of children	1.24	0.97
Schooling	years of schooling	14.25	2.17
Income	household income	79.11	55.63
Sample size		286	

Table 2. Beach Trips

		Trips Over Previous 12 Months		Trips Over Next 12 Months	
Variable	Label	Mean	Std Dev	Mean	Std Dev
Trips	day or overnight trips	2.77	2.38	2.67	2.39
Nights	number of nights on most recent/next trip	3.09	1.60	3.03	1.57
Party	party size on most recent/next trip	3.94	1.31	3.99	1.39
Spend	spending on most recent/next trip	748.83	726.25	879.37	873.37
Sample		213		286	

Table 3. Stated Preference Question Scenarios Data Summary

Scenario	Question	Sample size	Yes	Added Cost (mean)	Slightly Salty	Moderately Salty	Very Salty
1	1	213	100%	0	0	0	0
	2	213	65%	$569	0	0	0
	3	139	49%	$1306	0	0	0
2	1	286	100%	0	0	0	0
	2	286	57%	$560	0	0	0
	3	164	52%	$1288	0	0	0
3	1	286	87%	0	45%	55%	0
	2	248	79%	0	0	0	100%
	3	196	50%	$724	0	0	100%

Table 4. Stated Preference Question Yes Responses by Cost Amount

	Yes1			Yes1f			Yes2			Yes2f			Yes3f		
Cost Amount	Yes	Total	%Yes	Yes	Total	%Yes	Yes	Total	%Yes	Yes	Total	%Yes	Yes	Total	%Yes
100	19	19	100				27	31	87				13	18	72
200	27	30	90				17	26	65				8	12	67
300	8	14	57				22	31	71				9	12	75
400	10	14	71				13	20	65				13	21	62
500	12	18	67				12	20	60				10	13	77
600	12	25	48				24	38	63				11	17	65
700	14	23	61				13	28	46				4	15	27
800	13	21	62				17	32	53				7	16	44
900	9	24	38				11	33	33				4	11	36
1000	15	25	60				8	27	30				5	15	33
1100				11	23	48				18	34	53	3	9	33
1200				12	27	44				20	37	54	1	4	25
1300				17	35	49				23	39	59	3	11	27
1400				11	27	41				11	22	50	3	11	27
1500				17	27	63				14	32	44	5	11	45
Total	139	213	65	68	139	49	164	286	57	86	164	52	99	196	51
χ^2(df)	30.92*** (9)			3.80 (4)			33.17*** (9)			1.73 (4)			26.94** (14)		

***p<0.01, **p<0.05

Table 5. Logistic regression model of overnight beach trips: Dependent variable is whether respondent would take a trip with higher cost and salty water

	Naïve			M&L			ECLC		
	Coefficient	SE[a]	z	Coefficient	SE	z	Coefficient	SE	z
Constant	2.369	0.444	5.34	2.872	0.131	21.97	3.171	0.163	19.45
Cost	-0.0021	0.0003	-7.06	-0.0049	0.0003	-20.01	-0.0056	0.0003	-17.83
Slightly salty	-0.268	0.106	-2.52	-0.837	0.333	-2.51	-1.192	0.341	-3.50
Moderately salty	-0.722	0.177	-4.08	-1.493	0.298	-5.01	-1.802	0.307	-5.86
Very salty	-0.939	0.207	-4.53	-1.625	0.194	-8.36	-2.822	0.400	-7.06
AIC	1943.00			1594.10			1581.40		
Model χ^2	402.99			753.88			770.52		
Sample size	286			286			286		
Panel size	2031			2031			2031		
	Class probabilities								
Full Preservation	100%			69%			40%		
Full non-attendance				31%			24%		
Cost non-attendance							8%		
Very salty non-attendance							29%		

[a]Clustered standard error.

Table 6. Truncated mean willingness to pay estimates

	Naïve			M&L			ECLC		
	Mean	SE	z	Mean	SE	z	Mean	SE	z
Base case	1172.65	6.04	3.72	593.68	27.97	21.223	572.27	25.26	22.65
WTP | Slightly	1057.30	313.09	3.38	437.56	58.46	7.48	375.55	50.72	7.40
WTP | Moderate	869.55	277.26	3.14	325.31	46.49	7.00	284.30	40.28	7.06
WTP | Very	784.48	288.65	2.72	304.19	26.84	11.33	157.25	40.53	3.88
ΔWTP | Slightly	-115.35	47.04	-2.45	-156.11	59.49	-2.62	-196.71	51.67	-3.81
ΔWTP | Moderate	-303.11	98.43	-3.08	-268.37	48.55	-5.53	-287.97	42.50	-6.78
ΔWTP | Very	-388.17	74.44	-5.21	-289.49	33.26	-8.70	-415.01	40.44	-10.26

Table 7. Drinking water quality and weighted willingness to pay at North Carolina Beaches			
	Percent of Beaches		
Salty taste	2040	2060	2080
Not Salty	45%	39%	6%
Slightly Salty	23%	6%	29%
Moderately Salty	16%	16%	10%
Very Salty	3%	6%	0%
No aquifer	13%	32%	55%
	WTP[a]		
Naïve Model	$995	$756	$537
ECLC Model	$430	$340	$210
[a]Willingness to pay for an overnight beach trip weighted by salty taste and visitation frequency.			

Table 8. Estimates of lost welfare[a]			
	Millions of 2021 Dollars		
Pessimistic Scenario	2040	2060	2080
Naïve Model	$490	$1,148	$1,752
ECLC Model	$401	$656	$1024
Optimistic Scenario	2040	2060	2080
Naïve Model	$152	$163	$271
ECLC Model	$266	$285	$474
[a]Losses are relative to baseline welfare of $3,232 million in the naïve model and $1,616 in the ECLC model.			

Appendix

Each location in Table A1 corresponds with a model location in Fiori and Anderson (2022) and overnight trips in our survey. In 2040, 45% of the model locations have viable fresh groundwater resources, but 13% have already lost a freshwater resource. By 2060, 32% of the model locations have lost their freshwater resource, while the percentage with fresh groundwater resources has dropped to 39%. By 2080, only those locations with low SLR rates and low to moderate permeability (e.g., Bald Head Island and Emerald Isle), or wide island widths and/or thicknesses and moderate to high SLR (e.g., Kitty Hawk, Buxton, and Ocracoke) retain their freshwater aquifers. Most other areas, an estimated 55%, are predicted to lose their groundwater resource.

Table A1. Modeled drinking water quality estimates based on Fiori and Anderson (2022)				
		Water Quality		
Beach	Trip Frequency (%)	2040	2060	2080
Corolla	8.04	Slightly Salty	No Aquifer	No Aquifer
Duck	1.05	Slightly Salty	Moderately Salty	No Aquifer
Kitty Hawk	4.55	Not Salty	Not Salty	Not Salty
Kill Devil Hills	2.45	Slightly Salty	Moderately Salty	No Aquifer
Nags Head	5.24	Moderately Salty	No Aquifer	No Aquifer
Rodanthe	0.35	No Aquifer	No Aquifer	No Aquifer
Waves	1.05	Very Salty	No Aquifer	No Aquifer
Salvo	0	No Aquifer	No Aquifer	No Aquifer
Avon	2.1	Moderately Salty	No Aquifer	No Aquifer
Buxton	1.05	Not Salty	Not Salty	Slightly Salty
Hatteras	3.85	Moderately Salty	No Aquifer	No Aquifer
Ocracoke	2.45	Not Salty	Not Salty	Slightly Salty
Fort Macon	0	Slightly Salty	Very Salty	No Aquifer
Atlantic Beach	8.74	Slightly Salty	Moderately Salty	No Aquifer
Pine Knoll Shores	2.1	Slightly Salty	Moderately Salty	No Aquifer
Salter Path	0	Moderately Salty	Very Salty	No Aquifer
Indian Beach	1.4	Moderately Salty	No Aquifer	No Aquifer
Emerald Isle	10.14	Not Salty	Not Salty	Not Salty
North Topsail Beach	2.8	Slightly Salty	Moderately Salty	No Aquifer
Surf City	3.5	No Aquifer	No Aquifer	No Aquifer
Topsail Beach	5.24	No Aquifer	No Aquifer	No Aquifer
Wrightsville Beach	6.99	Not Salty	Not Salty	Slightly Salty
Carolina Beach	12.94	Not Salty	Not Salty	Moderately Salty
Kure Beach	1.75	Not Salty	Slightly Salty	Moderately Salty
Fort Fisher	1.75	Not Salty	Slightly Salty	Moderately Salty
Caswell Beach	0.7	Not Salty	Not Salty	Slightly Salty
Yaupon Beach	0	Not Salty	Not Salty	Slightly Salty
Long Beach	1.05	Not Salty	Not Salty	Slightly Salty
Holden Beach	1.4	Not Salty	Not Salty	Slightly Salty
Ocean Isle Beach	5.24	Not Salty	Not Salty	Slightly Salty
Sunset Beach	2.1	Not Salty	Not Salty	Slightly Salty