Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

Crowne Plaza Washington National Airport Hotel
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April 23-24, 2007

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U.S. Environmental Protection Agency (EPA)
National Center for Environmental Economics (NCEE) and
National Center for Environmental Research (NCER)
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Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m.	**Registration**	
8:30 a.m. – 8:45 a.m.	**Introductory Remarks** Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development	
8:45 a.m. – 11:30 a.m.	**Session I: Benefits Transfer** Session Moderator: Steve Newbold, EPA, NCEE	
	8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
	9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University
9:45 a.m. – 10:00 a.m.	**Break**	
	10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
	10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
	10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
	11:00 a.m. – 11:30 a.m.	Questions and Discussion
11:30 a.m. – 12:45 p.m.	**Lunch**	

April 23, 2007 (continued)

12:45 p.m. – 3:30 p.m.	**Session II: Wetlands and Coastal Resources** Session Moderator: Cynthia Morgan, EPA, NCEE	
	12:45 p.m. – 1:15 p.m.	A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland
	1:15 p.m. – 1:45 p.m.	A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods David Scrogin, Walter Milon, and John Weishampel, University of Central Florida
1:45 p.m. – 2:00 p.m.	**Break**	
	2:00 p.m. – 2:30 p.m.	Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh John Whitehead and Pete Groothuis, Appalachian State University
	2:30 p.m. – 2:45 p.m.	Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds
	2:45 p.m. – 3:00 p.m.	Discussant: John Horowitz, University of Maryland
	3:00 p.m. – 3:30 p.m.	Questions and Discussion
3:30 p.m. – 3:45 p.m.	**Break**	
3:45 p.m. – 5:45 p.m.	**Session III: Invasive Species** Session Moderator: Maggie Miller, EPA, NCEE	
	3:45 p.m. – 4:15 p.m.	Models of Spatial and Intertemporal Invasive Species Management Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa
	4:15 p.m. – 4:45 p.m.	Policies for the Game of Global Marine Invasive Species Pollution Linda Fernandez, University of California at Riverside
	4:45 p.m. – 5:00 p.m.	Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds
	5:00 p.m. – 5:15 p.m.	Discussant: Lars Olsen, University of Maryland
	5:15 p.m. – 5:45 p.m.	Questions and Discussion
5:45 p.m.	**Adjournment**	

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation

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Abstract

In this paper, we examine the impact of beach erosion and erosion control on the demand for beach trips. A contingent behavior setting of a hypothetical erosion control program, which employs a conjoint design to identify a program's potential effects (visible structure, poorer sand quality and so forth) on the beach environment in addition to preventing erosion, is incorporated into an in-person beach trip survey. Our results show that the recreation benefits of preventing erosion can be offset by the losses associated with the negative effects of erosion control. We also find that the economic values of erosion control vary across beaches that provide different activities and services. The findings may be used by policy makers to design economically efficient erosion control programs for beaches according to their specific characteristics.

Key Words: Beach Erosion, Contingent Behavior, Conjoint Design, Activity Specific Recreation Demand

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Abstract

In this paper, we examine the impact of beach erosion and erosion control on the demand for beach trips. A contingent behavior setting of a hypothetical erosion control program, which employs a conjoint design to identify a program's potential effects (visible structure, poorer sand quality and so forth) on the beach environment in addition to preventing erosion, is incorporated into an in-person beach trip survey. Our results show that the recreation benefits of preventing erosion can be offset by the losses associated with the negative effects of erosion control. We also find that the economic values of erosion control vary across beaches that provide different activities and services. The findings may be used by policy makers to design economically efficient erosion control programs for beaches according to their specific characteristics.

1. Introduction

Ocean beaches are important natural resources. Beach-related recreational activities in coastal areas also contribute significantly to local economies. According to the U. S. Army Corps of Engineers, close to half of the United States beaches are experiencing significant erosion problems. Beach erosion can be caused by a combination of human-induced development, global rising of the sea level, occasional violent weather systems, and chronic sediment transport by waves. Beach erosion results in losses of recreational beaches, tourist-related business, ocean front properties, land for aquaculture, and wildlife habitat.

Various erosion control programs/plans have been implemented in U.S. coastal areas. Most of the available erosion control methods have multiple effects, both positive and negative, on the beach and its surrounding environment. For example, some erosion control programs require installation of visible structures that can affect both the aesthetics of beaches and the overall experience of the beach trip itself. It is also possible for certain erosion control methods to initiate or accelerate erosion on neighboring beaches or affect coastal wildlife habitat. Some programs that require maintenance and adjustments may result in restricted use of beaches over a period of time.[1] If these effects are not considered when developing erosion control programs, non-optimal choices can result.

There are many studies examining the effectiveness and economic values of beach protection/preservation (e.g., Curtis and Shows, 1984; Bishop and Boyle, 1985; Lindsay et al., 1992; U.S. Army Corps of Engineers, 1994; Stronge, 1995; Dobkowski, 1998). However, none of these studies emphasizes the potential multiple effects of erosion control methods on the coastal environment and the associated tradeoffs. In his review of the empirical literature on the

[1] See the web site of Program for the Study of Developed Shoreline at Duke University for a description of erosion control devices and potential effects, http://www.nicholas.duke.edu/psds/Stabilization/Categories.htm.

economic value of marine recreation, Freeman (1995) points out that very few economic valuation studies have been done with a focus on the role of qualitative attributes of beaches.

The purpose of this study is to examine the impact of erosion and erosion control on beach recreation. A typical erosion control program is designed for the purpose of alleviating the effects of erosion. However, as discussed, it can also change the beach features and environment, visible structure on a beach, degraded conditions for wildlife viewing and so forth, thus directly affecting individuals' trip decisions. Further, beach visitors may react to various negative impacts differently, and the reaction to the impacts may be influenced by the type of activities that the visitors are engaged in. The variation in recreation activity across users is an important issue, yet less frequently addressed in empirical studies of recreation demand. A single trip demand model for all trips to a particular site assumes that all trips share common activities (or a single activity). Smith (1991) emphasizes that individuals are expected to have different demands for site services when they undertake different activities. Parsons (2003) argues that the more dissimilar the uses are, the greater the need is to disaggregate the model by type of use. Beach users clearly participate in different activities and the effects of erosion and erosion control programs are likely to vary across individuals given their different uses of the beach. Failure to recognize the differential effects of erosion control on beach activities may result in biased welfare measures.

In this paper, the multiple effects of a beach erosion control program on the beach environment are viewed as the 'attributes' of the program, and their impacts on demand for beach trips are examined. Contingent behavior data regarding program preferences and future beach trips are collected by randomly interviewing visitors at eight beaches in New Hampshire (NH) and Maine (ME). In the survey, individuals are presented with hypothetical erosion control

programs that have varying effects on the beach environment. The conjoint questioning format enables us to value the potential negative effects of an erosion control program on recreational beach use. We also elicit detailed information on types of recreation activity and compile the beach characteristics database. These data are incorporated into our trip demand analysis. We estimate a pooled single site travel cost model ('pooled' across eight beaches) and a set of trip change equations to capture effects of erosion and control methods. Recreation values associated with erosion and erosion control are computed for various beaches that are characterized by their popular activities and services. We find that erosion control is not necessarily beneficial when the erosion is relatively small. Further, the same erosion control program can generate different recreation values at different beaches because of the heterogeneity across beaches.

The remainder of this paper is organized as follows. Section 2 describes the survey design and data collection. Section 3 presents the empirical model and the corresponding welfare measures. Section 4 discusses results of the data analysis and demonstrates the varying recreation values of erosion control across beaches due to different beach characteristics and recreational activities. Section 5 gives concluding remarks.

2. Conjoint Design of Contingent Behavior Beach Recreation Survey

We conducted three focus group meetings. These included seacoast residents, inland residents, and ocean front property owners in NH and southern ME. The purpose of these meetings was to investigate individuals' perceptions of beach erosion, erosion control devices and the impact of both on beach recreation. We found that most of the focus group participants were familiar with erosion control techniques. Most were supportive of the preservation of existing beaches through erosion control methods but were also concerned about the potential

side effects of erosion control devices such as dangers to swimmers, impact on wildlife, impact on aesthetics, and water quality decline. The cost of implementing erosion control devices was of little concern to participants. They also felt that it would be difficult to evaluate the impact of erosion and erosion control if particular beach uses were not clearly described.

Based on the results of the focus groups, we developed an in-person, contingent behavior survey using a conjoint design to depict possible combinations of the side effects (impact attributes) of erosion control. In the conjoint questions, we asked people if erosion and the 'multi-attribute' erosion control programs would affect the number of trips taken to the beach. Posters with information on erosion and erosion control were shown while the survey was administered to ensure a basic understanding of the issues.

The in-person interviews were conducted at eight beaches in NH and Southern ME in August, 2002. Three of the eight beaches are in NH. Individual trip information including size of party, length of stay, beach activities, and demographics was collected. Beach activities were grouped in advance according to the factor analysis results in an unpublished study by Leeworthy, Meade, and Smith (1987) and reproduced in Smith (1991). Respondents were asked to check all activity groups that applied to their trips. They were presented with a hypothetical scenario regarding erosion at the beach where they were interviewed and asked if they would consequently change their trip behavior in the following year. Respondents were then presented with two hypothetical erosion control programs (one at a time) that would prevent the stated erosion, but these erosion control programs could potentially alter the beach environment. Under the premise that all proposed erosion control programs could prevent erosion, each program was described according to a set of five potential effects on the beach environment. Respondents

were asked how their future beach trips would change with these erosion control programs. The five beach attributes affected by the programs include:

- visible structure (beach aesthetics)
- danger to swimmers
- wildlife viewing
- salt water quality
- sand quality.

The level of beach erosion and erosion control impact attributes were varied randomly across survey respondent according to an orthogonal main effects experimental design (Lorenzen and Anderson, 1993).[2] The design of erosion control programs is summarized in Table 1. In our contingent behavior analysis we use the following trip information from respondents:

- number of trips expected in the next year
- reported change in number of trips given a hypothetical level of beach erosion
- reported change in number of trips if an erosion control program (with certain impacts on beach environment) is put in place to prevent the beach erosion
- reported change in number of trips for an alternative erosion control program.

An example of our contingent behavior questions to elicit responses of reported changes in trips listed above is given in appendix A. We consider day trips only in this analysis.[3] Travel cost is assumed to be $0.35 per mile and the opportunity cost of travel time is assumed to be one third of the hourly wage rate (wage=Income/2080).[4] Table 2 summarizes the survey data and includes definitions of variables used in the regression analysis for the demand for day trips.

Approximately two-thirds of the survey respondents are NH or ME residents. On average, each survey respondent planned to take 17 trips in the following year. The median is 6 trips that the distribution is right skewed and close to ninety percent of respondents planned to

[2] Specifically, a 2-factorial main effects with 5 factors experimental design, accompanying 6 levels of erosion, is employed.
[3] The ratio of day to total trips in the previous year was used to divide a change in total number of trips in response to the contingent behavior questions into changes in numbers of day and overnight trips in the following year. This was necessary because we did not ask people to report separately their changes in day and overnight trips in the contingent behavior questions.
[4] The opportunity costs of on-site time are not computed due to unavailability of data.

take 20 trips or less. One of the six levels of erosion (1, 4, 7, 10, 15, 25 feet/year) was randomly presented to respondents with an average of 10 feet. On average, erosion lead to1.36 fewer trips per respondent with 78% reporting no change in trips. When an erosion control program was introduced to prevent the stated erosion and some potential negative effects of erosion control device were presented, respondents still took fewer trips but the impact was attenuated--respondents now reported taking on average 1.01 fewer trips with 82% reporting no change in trips. The responses indicate that erosion control can be desirable but the potential negative impacts on the beach environment can offset the benefits of erosion control.

The beach recreation activity groups (A1 – A7) are also summarized in Table 2. Respondents may participate in more than one activity group during the same beach visit. The majority of the survey respondents did on-beach activities (A3). Observing wildlife, sightseeing, and walking/jogging constituted the second most popular group of activities (A1). Table 3 provides additional summary of characteristics and activities by beaches. The eight beaches in the survey are, from South to North, Hampton Beach State Park, Hampton Main Beach, Wallis Sands State Park, Long Sands, Ferry Beach, Old Orchard Beach, Crescent Beach, and Reid Beach State Park. Seven of these beaches currently have some erosion control device in place including seawalls, jetties, and sand dunes. By examining the summary of activities of survey respondents at the eight beaches, the beaches differ by activities that the visitors engaged in. For example, visitors at Ferry Beach and Old Orchard Beach are more likely to engage in activities in the A4 group (fishing, etc.) and visitors at Wallis Sands are noticeably less likely to have activities in the A1 group (wildlife viewing, sightseeing, etc.). In addition, four of the beaches have over half of their visitors from out of state. The average travel distance of visitors varies from 39 miles (Ferry Beach) to over 100 miles (Old Orchard Beach). It is perceivable that beach

trip decisions are influenced by different characteristics and activities of beaches. If erosion and erosion control alter beach characteristics and activities, then the recreational impact of erosion and erosion control can differ across beaches. This is examined in the regression analysis.

3. Empirical Model and Welfare Measure

Our analysis involves three steps. First, we estimate a pooled single site recreation demand model using data on the total number of expected recreation trips next year as our dependent variable. Our focus in this step is on estimating the coefficient on travel cost which is used in our welfare analysis in step three. Second, we estimate two trip-change equations to predict how the demand for trips shifts with changes in erosion and erosion control programs. These models use the changes in day trips from our contingent behavior questions as dependent variables. Third, we use the quantity changes predicted in the second step and the travel cost coefficient in the first step to compute welfare measures using conventional welfare analytic methods.

We use a Poisson regression to estimate the demand function in the first step. An on-site, in-person survey ensures participation in the beach recreation of survey respondents. However, the random sample obtained on site does not readily represent the relevant population because those who visit the site more frequently are more likely to be sampled and an on-site sample does not include those who take zero trip in the studied period. To correct for the on-site sampling bias and truncation, we employ the model proposed by Shaw (1988) and use the following form in estimation

$$\Pr ob(Y_i = y_i) = \frac{e^{-\lambda_i} \lambda_i^{(y_i - 1)_t}}{(y_i - 1)!} \quad y_i = 1, 2, ... \qquad (1)$$

where Y_i is the quantity demanded for beach trips by individual i and λ_i is the expected value of Y_i. The above model resembles the standard Poisson model except for the subtraction of 1 from y_i. As usual, λ_i depends on the price of Y and individual characteristics.[5] Since our survey was conducted in eight different beaches in New Hampshire and Maine, we have a 'pooled' model which allows for variation in site characteristics. So, λ_i is specified to depend on beach characteristics as well.

$$\ell n\lambda_i = \alpha + \beta_p Cost_i + \beta' X_i + \gamma' W_i \qquad (2)$$

where $Cost_i$ is the total travel cost per trip; X_i is a vector of individual i's characteristics including recreation activities at the beach; W_i is a vector of beach characteristics faced by the individual i; and α, β_p, β, and γ are parameters to be estimated.

As noted earlier, each respondent was asked a contingent behavior question about increased erosion and then two more questions about the installation of erosion control devices to forestall the erosion. In all cases, respondents were asked how they would adjust their trips in response to the hypothetical changes. We estimate two Poisson trip-change equations in step 2 – one for the erosion scenario and one for the two erosion control programs that prevent the erosion.

The basic form of the Poisson trip change models is $\Pr(M_{ji} = m_{ji}) = \frac{e^{-\omega_{ji}} \omega_{ji}^{m_{ji}}}{m_{ji}!}$, j=1,2. Let C_{1i} be the change in number of day trips due to erosion and C_{2i} be the change in number of day trips assuming the erosion is mitigated by erosion control and that there are some (negative)

[5] We estimated the Negative Binomial model without the correction for the on site sampling bias. The model fit was not as good as the Poisson model. We also attempted the estimation of the Negative Binomial model with the correction for truncation and on site sampling bias (Englin and Shonkwiler, 1995) and encountered convergence difficulties. Based on the model fit and stability, we chose to report the Poisson results in this paper.

impacts associated with that control. The expected values of the trip changes are specified as follows:

$$\omega_{1i} = \ell n(\overline{C}_{1i} + 1) = \delta_1 E_i + \delta_2 E_i/\text{Width}_j + \eta'(E_i{*}A_i) + \mu'(E_i{*}W_i) + \varphi'(E_i{*}X_i) \quad (3)$$

$$\omega_{2i} = \ell n(\overline{C}_{2i} + 1) = \kappa'\text{ATT}_i + \theta'(\text{ATT}_i{*}A_i) + \nu'(\text{ATT}_i{*}W_i) + \psi'(\text{ATT}_i{*}X_i) + \tau E_i/\text{Width}_j \quad (4)$$ [6]

where $\overline{C}_{1i}$ is the expected value of C_{1i}; E_i is the hypothesized level of beach erosion faced by individual i and Width_j is the width of beach j in high tide to assess the severity of suggested erosion; A_i is a vector of beach activity groups (that in this study, 7 beach activity groups A=[A1, A2,…,A7]′ are identified); $\overline{C}_{2i}$ is the expected value of C_{2i}; ATT is the vector of impact attributes appearing in the conjoint question (visible structure, swim danger, wildlife impact, water quality, and sand quality); and δ_1, δ_2, η, μ, φ, κ, θ, ν, and ψ are parameters to be estimated.

The stated level of erosion (E) and the vector of impact attributes of an erosion control program (ATT) are the sole factors to induce the changes in trips in our conjoint questions. Consequently E is interacted with all explanatory variables in Equation (3) and ATT is interacted with all explanatory variables in Equation (4) except for the erosion severity variable E/Width. In the survey, respondents were told that the implementation of an erosion control program would prevent the occurrence of the stated erosion. However, the respondents could still be influenced by the stated severity of erosion even though it was eradicated by erosion control. For example, some survey respondents could be skeptical about the effectiveness of the proposed erosion control program if the stated severity of erosion was high. Because of the order of questions in the survey, the response to erosion control could also be influenced by the previous response to erosion. There might be other unobserved factors associated with the stated erosion level that affected the response

to erosion control. Therefore, the erosion severity variable E/Width is included in Equation (4) as a testable hypothesis whether the trip change in response to erosion control is influenced by the hypothesized severity of erosion.

There is no intercept term in each of the trip change equations; this coupled with the addition of 1 on the left hand side of the equations to ensure that $\overline{C}_1$=0 when E=0 and $\overline{C}_2$=0 when ATT=0. Beach erosion and negative impacts of erosion control on the beach environment are in general perceived as "bad" in that the vast majority of beach goers responded by taking fewer trips. Less than one percent of the sample reported that they would increase their trips if erosion occurred. We deleted these observations from our sample.[7] The predicted trip changes (reductions) are computed from the estimation results of Equations (3) and (4) as $\hat{C}_{ji} = e^{\hat{\omega}_{ji}} - 1$, where j=1,2.

The expected quantity demanded for beach trips takes on a semi-log functional form (Equation (2)). As Hellerstein and Mendelsohn (1993) and Whitehead, et. al. (2000) show with this form of demand, the change in consumer surplus (ΔCS) due to a quality change is

$$\Delta CS = \frac{\hat{C}}{\hat{\beta}_p} \tag{5}$$

where $\hat{C}$ is the predicted change in the number of beach trips due to the introduction of the hypothetical erosion or erosion control scenario, estimated using Equations (3) and (4). $\hat{\beta}_p$ is the coefficient on travel cost and is estimated using equation (1). In the final step of our analysis, a variety of scenarios, varying degree of erosion and impact of erosion control will be considered

[6] In Equation (4), the notations are used for easier comprehension. Algebraically the expressions (ATT_i*A_i), (ATT_i*W_i), and (ATT_i*X_i) should be written as (ATT_iA_i'), (ATT_iW_i'), and (ATT_iX_i'), respectively.

[7] It is debatable to exclude those who wanted to take more trips in response to the increased erosion in the analysis. In this paper, we exclude these observations to enable the use of the Poisson model to analyze the trip reductions due to erosion and erosion control.

for each of the eight studied beaches. Each scenario gives rise to a $\hat{C}$ and all use equation (5) to compute the welfare change.

4. Estimation Results

We estimate the demand for trips with corrections for on-site sampling bias and truncation using the Equations (1) and (2). For comparison, we also estimate the Poisson model without corrections for truncation and endogenous stratification. The results of both models, Model 1 without correction and Model 2 with correction, are reported in Table 4. In both models the coefficient of the travel cost variable is negative and significant as expected. Activity groups (A1 – A7) are included in the models. Each activity group is indicated by a keyword in Table 4, and the subsequent tables. The complete list of activities in each group is given in Table 2. All groups of beach activities significantly influence the demand for trips in different degrees. Ocean-front property owners and retirees take significantly more beach trips. Households with more adults or more children under an age of 13, take fewer beach trips. Sufficient bathhouse facilities (BathSuf) are important to trip decisions. The width of beach at high tide also matters. Beach goers tend to take fewer trips to those beaches with sand dunes and jetties, providing evidence that beach trip decisions are affected by the impacts of erosion control on the beach environment. Finally, the estimated coefficient of the travel cost variable is -0.013 in Model 1 and -0.014 in Model 2. The difference is small and marginally significant at the 0.1 level (Wald test statistic χ^2=2.87[1 d.f.]). We use the estimated coefficient of the cost variable from Model 2, the model corrected for on-site sampling bias, to perform the subsequent welfare analysis.

The trip change equation associated with erosion (Equation (3)) is estimated with two specifications. The explanatory variables in the *basic* model include only the proposed level of

erosion and the relative size of erosion (as a proportion of the width of the beach at high tide). It describes the average impact of erosion on recreation for all beaches. The augmented *activity specific* model explores the differential effects of erosion on trip decisions according to individual specific beach uses by adding explanatory variables that interact erosion with groups of beach activities, as well as the interactions of erosion with location of the respondent's home and the presence of erosion control device. The estimation results are reported in Table 5. Note that the dependent variable indicates *fewer* trips taken as a result of beach erosion, so a positive coefficient on the erosion variable implies a reduction in beach trips when erosion occurs. As seen, erosion significantly reduces recreation trips. The relative size of erosion is not significant in the *basic* model but it becomes significant with twice as large magnitude in the *activity specific* model in which the heterogeneity of beaches is addressed. Most of the interaction terms are significant in the *activity specific* model, indicating that the magnitude of erosion impact on trip decisions depends on the individual beach activities and beach characteristics.

Based on the estimation results in Tables 4 and 5, and the summary of beach characteristics in Table 3, we compute the average changes in consumer surplus for two levels of beach erosion: one foot (slight) and ten feet (moderate) erosion, and report the estimates by beaches in Table 6.[8, 9] According to the *basic* model, the average change in consumer surplus per visitor per year is approximately $4 for one foot of erosion and $50 for ten feet of erosion. The welfare measures do not vary significantly across beaches since they are distinguished only by the relative size of erosion in the *basic* model. The *activity specific* model differentiates the beaches by the corresponding activities and characteristics. Based on the *activity specific* model,

[8] The general formula to compute the change in consumer surplus is: $(e^{\hat{\delta}_1 E + \hat{\delta}_2 E/Width + \hat{\eta}' E*A + \hat{\mu}' E*W + \hat{\phi} E*X} - 1)/\hat{\beta}_p$, where average values of the variables for each beach, as described in Table 3, are inserted in the formula.

the average changes in consumer surplus are quite different among the studied beaches. The benefits per visitor per year range from $1.7 (Hampton Main Beach) to $6.8 (Ferry Beach) for preventing one foot of erosion, and from $19.5 to $105.4 for preventing 10 feet of erosion. In general, the change in consumer surplus differs significantly across beaches. Every beach has its own characteristics and endowments, and attracts visitors to come for different activities. Taking into account the beach activities and characteristics helps discern the welfare effects of erosion on different beaches.

The regression analyses for trip reductions from the possible negative beach effects of erosion control (Equation (4)) are given in Table 7. The dependent variable indicates *fewer* trips taken due to the negative effects of erosion control so a positive coefficient estimate indicates a trip reduction. We first report a *basic* model that only includes the impact attributes (ATT1 – ATT5) of erosion control and the relative size of erosion as explanatory variables. In the *basic* model, all five impacts of erosion control significantly cause reduction of beach trips. The effect of erosion control on reduction of wildlife viewing has the largest impact on reducing beach trips. The variable of relative size of erosion is also significant, indicating that there are unobserved factors associated with the stated erosion to cause a significant reduction of future beach visits even when erosion control is in place to prevent the stated erosion. An augmented *activity specific* models interacting impact attributes with beach activities and characteristics is also reported.[10] The results show that if sand dunes are currently present, the trip reduction caused by visible structure due to erosion control is enhanced (positive coefficient on ATT1*SandDune). Conversely, beach visitors are less concerned about visible structure from

[9] In stead of welfare measures by beaches, we may compute changes in consumer surplus by activities. We report welfare measures by beaches to demonstrate the feasibility of using our models to derive welfare measures for any beach with a set of characteristics.

erosion control when a seawall is already present at the beach (negative coefficient on ATT1*SeaWall) possibly because visitors have grown accustomed to the visible seawall. The impact of erosion control attributes on trip changes depends on individual beach uses. For examples, those who come to beach to fish and camp are not adversely affected by visible erosion control devices (negative coefficient on ATT1*A4); those who come to enjoy the nature will take fewer trips if erosion control will result in a significantly less wildlife sighting (positive coefficient on ATT3*A1); those who engage in boating and kayaking will take fewer trips if water quality is affected by erosion control (positive coefficient on ATT4*A6). Similar to the *basic* model, the change in beach visits in response to erosion control is significantly affected by the stated relative size of erosion.

The changes in consumer surplus from the effects of erosion control by beaches based on the *basic* model are computed and reported in Table 8A. For comparison, we again compute welfare measures for two levels of stated erosion, one foot and ten feet. According to the *basic* model, given the stated erosion level to be one foot, on average the annual loss of consumer surplus per visitor from an erosion control program is approximately $15 if the program requires building a visible structure (ATT1), $19 if it results in a chance of minor injury to swimmers (ATT2), $23 if it reduces wildlife viewing (ATT3), $9 if deterioration of salt water quality results (ATT4), and $20 if sand quality is affected (ATT5). An erosion control device may have multiple impacts. For example, a jetty is visible and can affect water quality (ATT1 & ATT4) that on average the change in consumer surplus is about $25. If an erosion control device affects wildlife viewing and sand quality (ATT3 & ATT5) such as sand dunes, then the overall change in consumer surplus per visitor per year is approximately $49. Welfare effects for other

[10] In total, thirty-five attribute-activity interaction terms can be included in the estimation. We "trimmed" the specification by including the terms that are plausible and significant.

combinations of impact attributes can also be computed. Note that the change in consumer surplus of multiple impacts is not the sum of welfare changes from the individual impacts because of the nonlinearity in the Poisson model. Also, there is no significant difference of surplus changes across beaches for a hypothesized one-foot erosion. For a stated ten-foot erosion, on average the loss of consumer surplus for each of the erosion control impacts increases to about $22, $28, $32, $17, and $30, respectively. The annual per-person loss in consumer surplus averages about $35 if an erosion control program results in both visible structure and deteriorated water quality, and the average loss of per-person consumer surplus is close to $61 if reduced wildlife viewing and lower sand quality result from the erosion control program. We also see differences in surplus changes across beaches. Under the hypothesized 10 feet of erosion, the negative effects of erosion control will result in the largest losses at Crescent Beach and smallest losses at Old Orchard Beach.

Comparing the changes in consumer surplus from erosion in Table 6 and from erosion control in Table 8A, it is clear that when the erosion is slight (e.g., 1 foot), erosion control is not beneficial since the losses of erosion do not outweigh the losses from the negative effects of erosion control. When erosion is moderate, erosion control can be beneficial. The shaded cells in Table 8A indicate the cases where losses of erosion are larger than the losses from the negative effects of erosion control. When erosion is 10 feet, any erosion control device that causes only one of the five negative effects generates an overall positive benefit at any of the beaches. However, erosion control programs that induce multiple negative effects are not necessarily desirable. For example, an erosion control program with a visible structure and reduced water quality is still beneficial at all eight beaches, while an erosion control program with reduced wildlife viewing and sand quality is not. The results show that certain negative impacts of

erosion control are worse than the other. Reducing wildlife viewing is considered by beach visitors the most negative impact of erosion control. The findings suggest that certain erosion control devices are preferred by visitors for their less negative effects on beach environment.

Based on the *activity specific* model, the computed changes in consumer surplus associated with impact attributes of erosion control by beaches are reported in Table 8B. Among the five impact attributes, reduced wildlife viewing remains to be the most devastating impact of erosion control on recreation. The average annual per-person loss of reduced wildlife viewing due to erosion control is about $24 for a stated one-foot erosion and $31 for a ten-foot erosion.[11] Comparing across beaches, the recreation impact of the five effects of erosion control differs. For examples, adding a visible structure for erosion control causes the smallest loss in recreation value at Hampton Main Beach where seawall is already present and incurs the largest loss at the more natural Crescent Beach; deterioration of water quality results in more losses of recreation values at Wallis Sands and Ferry Beaches than at Old Orchards Beach; Ferry Beach incurs the largest loss of recreation value with a combination of visible structure and lower water quality from erosion control.

Comparing the welfare losses of erosion and losses from the negative effects of erosion control (the bottom half of Table 6 and Table 8B), the net welfare effect depends on the amount of erosion that is controlled. The net welfare effects of erosion control to prevent one foot of erosion will always be negative since the estimated losses of erosion control are larger than the losses of erosion. When erosion is 10 feet, the shaded cells in Table 8B indicate the cases where erosion control generates overall positive recreational benefits. For examples, an erosion control program with a visible device will have positive recreational benefits at most beaches except for

Hampton Beach State Park and Reid State Park; a program that reduces wildlife viewing will not be beneficial at five out of the eight beaches; all beaches will benefit from erosion control if the only negative effect is slight deterioration of water quality; half of the beaches will still have positive recreational benefits from erosion control when it results in visible structure and reduced water quality but only two beaches benefit from erosion control if it affects wildlife viewing and sand quality.[12] In sum, erosion control can be beneficial to prevent moderate to severe erosion that the welfare loss associated with the erosion is likely to exceed the loss due to erosion control disamenities. However, for small amounts of erosion, erosion control programs may bring on larger negative effects than the erosion itself.

5. Conclusion

We designed contingent behavior, in-person survey to value beach erosion control and employed a conjoint design in formulating the hypothetical erosion control to take into account the impacts of erosion control on the beach environment. The differential effects of erosion and erosion control on individual trip decisions due to varying trip activities and beach characteristics were demonstrated. We find that on average the loss of consumer surplus for a 10-foot erosion is approximately $50 per person, per year. However, this welfare loss is not completely recovered by erosion control due to potential negative effects of erosion control on the beach environment. The benefits of erosion control can be exaggerated if these negative erosion control effects are ignored. Further, the changes in consumer surplus due to erosion and erosion control vary with

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[11]As discussed previously, we find that relative size of erosion affects trip decisions even after the alleged erosion is to be prevented by erosion control. Consequently welfare measures associated with the negative effects of erosion control vary with the relative size of erosion.

[12] We also compute the changes in consumer surplus for a 25-foot (severe) erosion. As expected, erosion control generates overall positive recreational benefits at all beaches. We also examine the "critical size" of erosion at which a specific erosion control program becomes beneficial for each of the studied beaches. For example, for the erosion

individual beach activities and characteristics. Our findings reiterate the importance of distinguishing the purposes of recreational trips and incorporating beach characteristics in the welfare analysis of beach erosion control. The proposed survey questioning format and estimation strategies give rise to program and beach specific welfare measures that may be used by policy makers to design economically efficient erosion control programs at locations facing different beach uses.

In this paper, we study the impact of erosion control on the demand for day trips. It is expected that the effects of erosion on the demand for over-night trips will differ and will be studied in the future. Also, the focus of this study is the use value of beach erosion control. Huang and Poor (2005) find that beach preservation is valued by the general public for its contribution to property protection, protection of wildlife habitat, etc. The total benefits of beach erosion control must take into account both the use and non-use values, and further research to combine these values is warranted.

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control program that causes lower sand quality to be beneficial at Crescent Beach, the erosion has to be at least 6.5 feet. All these results are available upon request from authors.

References

Bishop, Richard C. and Kevin Boyle, "The Economic Value of Illinois Beach State Nature Preserve," Final Report to Illinois Department of Conservation, 1985, Madison, WI: HBRS.

Curtis, T. D. and E. W. Shows, "A Comparative Study of Social Economic Benefits of Artificial Beach Nourishment--Civil Works in Northeast Florida," Department of Economics Report, Tampa, University of South Florida.

Dobkowski, Aleksandra H., "Dumptrucks Versus Dredges: An Economic Analysis of Sand Sources for Beach Nourishment," *Coastal Management*, Vol. 26, No. 4, 1998: 303.

Englin, Jeffrey and J. Scott Shonkwiler, "Estimating Social Welfare Using Count Data Models: An Application to Long-Run Recreation Demand Under Conditions of Endogenous Stratification and Truncation," *Review of Economics and Statistics* 77, No.1, 1995: 104-112.

Freeman, A. Myrick III, "The Benefit of Water Quality Improvement for Marine Recreation: A Review of the Empirical Evidence," *Marine Resource Economics*, Vol. 10, 1995: 385-406.

Hellerstein, Daniel and Robert Mendelsohn, "A Theoretical Foundation for Count Data Models," *American Journal of Agricultural Economics*, Vol. 75, No. 3, 1993: 604-611.

Huang, Ju-Chin and P. Joan Poor, "Welfare Measurement with Individual Heterogeneity: Economic Valuation of Multi-Attribute Beach Erosion Control Programs," working paper, University of New Hampshire, 2005.

Lindsay, Bruce E., John M. Halstead, Helen C. Tupper, and Jerry J. Vaske, "Factors Influencing the Willingness to Pay for Coastal Beach Protection," *Coastal Management*, Vol. 20, No. 3, 1992: 291-302.

Lorenzen, Thomas J. and Virgil L. Anderson, *Design of Experiments—A No Name Approach*, 1993 (Marcel Dekker, Inc., New York).

Parsons, George R., The Travel Cost Model, Chapter 9 in A Primer on NonMarket Valuaiton (eds. Champ, Boyle, and Brown), 2003

Shaw, Daigee, "On-site Samples' Regression: Problems of Non-negative Integers, Truncation, and Endogenous Stratification," *Journal of Econometrics*, Vol. 37, 1988: 211-223.

Smith, V. Kerry, "Household Production Functions and Environmental Benefit Estimation," in *Measuring the Demand for Environmental Quality*, John B. Braden and Charles D. Kolstad, eds., Elsevier Science Publishers (North-Holland), 1991.

Stronge, William B., "The Economics of Government Funding for Beach Nourishment Projects: The Florida Case," *Shore & Beach*, Vol. 63, No. 3, 1995.

U.S. Army Corps of Engineers, "Shoreline Protection and Beach Erosion Control Study: Phase I: Cost Comparison of Shoreline Protection Projects of the U.S. Army Corps of Engineers," WRSC-IWR, 1994.

Whitehead, John C., Timothy C. Haab, and Ju-Chin Huang, "Measuring Recreation Benefits of Quality Improvements with Revealed and Stated Behavior Data," *Resource and Energy Economics*, Vol. 22, No. 4, 2000: 339-354.

TABLE 1
Assigned Levels of Erosion and Erosion Control Effects in the Conjoint Design

Attributes of an Erosion Control Program (Variable Name)	**Levels**
Erosion	1, 4, 7, 10, 15, 25 (Feet/Year)
Visible structure on beach (**ATT1**)	Yes, No
1/1000 chance of minor injury to swimmers (**ATT2**)	Yes, No
Wildlife viewing reduced by 50% (**ATT3**)	Yes, No
Deterioration (10%) of salt water quality near beach (**ATT4**)	Yes, No
Sand quality: coarser sand with small rocks (**ATT5**)	Yes, No

TABLE 2
Variable Definition and Summary Statistics

Variable	Definition	N	Mean	Std Dev
DTripNY	Planned number of day trips in the following year	459	17.000	35.464
C_1	Decline in planned number of day trips due to erosion (22.2% of respondents reported nonzero decline)	459	1.362	5.200
C_2	Decline in planned number of day trips due to negative impacts of erosion control devices on beach environment (18.5% of respondents reported nonzero decline)	918	1.021	3.315
TtripTY	Total number of trips in the year of interview	459	17.431	33.460
TimeCost	Travel time cost ($) [=(income/2080)*hours*2]	459	14.428	16.345
TranCost	Out-of-pocket travel cost ($) [=$0.35*distance*2]	459	35.616	26.410
Cost	Total travel cost ($) [=TimeCost+TranCost]	459	50.044	38.427
SmlKids	Number of children under 13 of age in the household	459	0.625	0.955
Adults	Number of adults in the household	459	2.102	1.118
Income	Annual household income	459	59489	28088
NH	=1 if NH resident	459	27.7%	
ME	=1 if ME resident	459	39.7%	
Resident	=1 if resident of the state where the beach is located in	459	60.6%	
Distance	Travel distance (100 miles)	459	0.509	0.377
Ocean	=1 if own ocean front property	459	3.9%	
Retire	=1 if retired	459	10.0%	
A1	=1 if trip involved wildlife observation, photography, sightseeing, walking/jogging, bicycling, driving	459	61.9%	
A2	=1 if trip involved sports, concerts/plays, festivals, museums, hiking/trailing, horseback riding, back packing	459	19.2%	
A3	=1 if trip involved swimming, surfing, picnicking, family gathering, sunbathing, shell collecting	459	94.8%	
A4	=1 if trip involved camping, fishing	459	9.2%	
A5	=1 if trip involved pool swimming, golfing, tennis	459	8.9%	
A6	=1 if trip involved boating, canoeing, kayaking, sailing, water skiing	459	11.3%	
A7	=1 if trip involved theme parks, casinos	459	12.6%	
SandDune	=1 if sand dunes present at site	459	3 beaches	
Seawall	=1 if seawalls present at site	459	4 beaches	
Jetty	=1 if jetties present at site	459	2 beaches	
BathSuf	=1 if bath facilities sufficient according to beach manager	459	6 beaches	
Length	Length of beach (1000 ft)	459	5.101	5.104
WidthLT	Width of beach at low tide (100 ft)	459	2.858	1.356
WidthHT	Width of beach at high tide (100 ft)	459	0.761	0.356
SandQ	=1 if sand quality is good according to beach manager =0 if sand quality is ok or poor	459	86.5%	
Erosion	Proposed level of erosion [=1,4,7,10,15,25 ft]	459	10.211	7.646
EroRtLT	Ratio of proposed erosion to width of beach at low tide	459	0.051	0.060
EroRtHT	Ratio of proposed erosion to width of beach at high tide	459	0.179	0.189

TABLE 3
Summaries of Characteristics and Activities by Beaches

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
WidthHT (width at high tide (ft))	82.5	82.5	100	35	50	150	30	115
Resident (% of visitors are residents)[a]	32.8%	13.0%	71.0%	7.6%	84.4%	33.7%	79.7%	96.7%
Distance (average travel distance, 100 miles)[a]	0.601	0.673	0.667	0.751	0.390	1.001	0.462	0.493
A1 (nature)[a]	62.6%	62.9%	34.5%	50.3%	73.1%	73.1%	52.9%	71.7%
A2 (sports)[a]	13.1%	38.4%	17.6%	8.1%	41.4%	21.2%	10.2%	20.5%
A3 (sunbath)[a]	95.8%	98.4%	97.1%	83.9%	100.0%	100.0%	96.7%	90.7%
A4 (fish)[a]	6.1%	2.2%	4.7%	3.8%	15.7%	17.1%	9.2%	13.1%
A5 (golf)[a]	6.5%	12.7%	2.8%	5.6%	10.2%	18.4%	6.5%	13.1%
A6 (boat)[a]	14.9%	6.0%	2.1%	1.4%	14.8%	7.8%	11.1%	15.3%
A7 (park)[a]	6.7%	38.3%	5.3%	7.4%	6.0%	12.6%	0.7%	12.2%
Sea Wall (=1 if seawalls present)	1	1	1	1	0	0	0	0
Sand Dune (=1 if sand dunes present)	1	0	0	0	0	0	1	1
Jetty (=1 if jetties present)	0	0	1	0	1	0	0	0

a The summary statistic is weighted by the visit frequency: $\sum_{i=1}^{n} \frac{x_i}{trip_i} \Big/ \sum_{i=1}^{n} \frac{1}{trip_i}$, where x_i is the characteristic or activity variable, and $trip_i$ is the total number of trips taken by individual i.

TABLE 4
Estimated Demand for Beach Trips

Dependent Variable: DTripNY		
	Model 1 (without correction)	Model 2 (with correction for truncation and on-site sampling bias)
Intercept	3.534*** (0.103)	3.534*** (0.107)
Cost	-0.013*** (0.0005)	-0.014*** (0.0005)
A1 (nature)	0.244*** (0.028)	0.261*** (0.029)
A2 (sports)	0.390*** (0.029)	0.416*** (0.030)
A3 (sunbath)	-0.546*** (0.043)	-0.582*** (0.044)
A4 (fish)	0.375*** (0.042)	0.403*** (0.043)
A5 (golf)	-0.335*** (0.047)	-0.356*** (0.049)
A6 (boat)	0.136*** (0.037)	0.136*** (0.038)
A7 (parks)	0.080** (0.039)	0.083** (0.040)
Ocean	1.186*** (0.033)	1.207*** (0.033)
SmlKids	-0.099*** (0.015)	-0.110*** (0.015)
Adults	-0.095*** (0.012)	-0.102*** (0.013)
Retire	0.262*** (0.031)	0.275*** (0.032)
Resident	0.451*** (0.035)	0.467*** (0.036)
SandDune	-1.253*** (0.071)	-1.352*** (0.074)
SeaWall	0.019 (0.045)	0.00042 (0.047)
Jetty	-0.716*** (0.068)	-0.771*** (0.071)
BathSuf	0.474*** (0.051)	0.515*** (0.053)

Length	-0.001 (0.005)	-0.003 (0.005)
WidthHT	0.096* (0.052)	0.121** (0.054)
LLF N	-5054.881 459	-5261.089 459

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 5
Estimated Trip Changes When Erosion Occurs

Dependent Variable: log(C_1+1)		
	Basic Model	***Activity Specific Model***
Erosion	0.050*** (0.004)	0.043** (0.017)
Erosion/WidthHT	0.294 (0.204)	0.647** (0.271)
Erosion*A1 (nature)		0.006 (0.005)
Erosion*A2 (sports)		0.001 (0.006)
Erosion*A3 (sunbath)		0.023* (0.012)
Erosion*A4 (fish)		-0.016** (0.008)
Erosion*A5 (golf)		-0.024*** (0.009)
Erosion*A6 (boat)		0.068*** (0.006)
Erosion*A7 (parks)		-0.027*** (0.009)
Erosion*Resident		-0.009 (0.006)
Erosion*Distance		-0.038*** (0.008)
Erosion*SeaWall		-0.016*** (0.005)
Erosion*SandDune		-0.014** (0.007)
Erosion*Jetty		0.027*** (0.007)
LLF	-1452.370	-1355.272
N	459	459

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 6
Annual Per-Person Losses from Beach Erosion ($)

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
The Basic Model								
1 foot of Erosion	3.932	3.932	3.885	4.300	4.108	3.810	4.406	3.856
	(0.236)	(0.236)	(0.251)	(0.270)	(0.218)	(0.281)	(0.320)	(0.262)
10 feet	50.565	50.565	49.803	56.638	53.437	48.615	58.452	49.337
	(3.549)	(3.549)	(3.795)	(4.235)	(3.259)	(4.272)	(5.178)	(3.970)
The Activity Specific Model								
1 foot of Erosion	1.818	1.746	3.702	2.529	6.791	2.028	3.988	2.389
	(0.410)	(0.390)	(0.405)	(0.470)	(0.468)	(0.596)	(0.365)	(0.435)
10 feet	20.392	19.498	46.897	29.693	105.445	23.059	51.479	27.805
	(5.119)	(4.832)	(6.235)	(6.384)	(9.729)	(7.642)	(5.756)	(5.806)

Note: Standard errors are in the parentheses.

TABLE 7
Estimated Trip Changes in Response to Effects of Erosion Control on Beach Environment

Dependent Variable: log(C_2+1)		
	Basic Model	***Activity Specific Model***
ATT1 (=1, visible structure)	0.179*** (0.045)	0.217** (0.093)
ATT2 (=1, swim danger)	0.230*** (0.045)	0.260*** (0.046)
ATT3 (=1, wildlife viewing ↓)	0.268*** (0.045)	0.089 (0.069)
ATT4 (=1, water quality ↓)	0.115** (0.045)	0.138* (0.076)
ATT5 (=1, sand quality ↓)	0.245*** (0.047)	0.173*** (0.052)
ATT1*A4 (fish)		-0.357*** (0.136)
ATT1*SeaWall		-0.175** (0.074)
ATT1*SandDune		0.167** (0.085)
ATT1*Jetty		0.101 (0.106)
ATT2*A7 (parks)		-0.230** (0.108)
ATT3*A1 (nature)		0.316*** (0.080)
ATT4*A1 (nature)		-0.147* (0.082)
ATT4*A4 (fish)		-0.222 (0.137)
ATT4*A6 (boat)		0.354*** (0.101)
ATT4*Jetty		0.244*** (0.092)
ATT5*A2 (sports)		-0.382*** (0.089)
ATT5*A4 (fish)		0.968*** (0.131)
Erosion/WidthHT	0.617*** (0.105)	0.520*** (0.108)
LLF	-2138.326	-2072.547
N	918	918

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 8A
Annual Per-Person Losses due to Effects of Erosion Control on Beach Environment ($)
- The Basic Model

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
Losses due to negative effect(s) of erosion control to prevent 1 foot of erosion								
ATT1 (=1, visible structure)	14.720	14.720	14.606	15.603	15.142	14.429	15.861	14.537
	(3.950)	(3.950)	(3.947)	(3.981)	(3.964)	(3.941)	(3.991)	(3.945)
ATT2 (=1, swim danger)	19.207	19.207	19.088	20.136	19.651	18.901	20.407	19.015
	(4.098)	(4.098)	(4.095)	(4.128)	(4.111)	(4.090)	(4.137)	(4.093)
ATT3 (=1, wildlife viewing ↓)	22.738	22.738	22.614	23.703	23.199	22.420	23.985	22.538
	(4.293)	(4.293)	(4.289)	(4.324)	(4.307)	(4.284)	(4.335)	(4.287)
ATT4 (=1, water quality ↓)	9.354	9.354	9.248	10.182	9.750	9.081	10.424	9.182
	(3.688)	(3.688)	(3.684)	(3.716)	(3.700)	(3.679)	(3.725)	(3.682)
ATT5 (=1, sand quality ↓)	20.647	20.647	20.526	21.591	21.098	20.336	21.866	20.452
	(4.386)	(4.386)	(4.382)	(4.420)	(4.402)	(4.377)	(4.431)	(4.380)
ATT1=1 & ATT4=1	25.261	25.261	25.134	26.252	25.735	24.935	26.541	25.056
	(5.805)	(5.805)	(5.801)	(5.841)	(5.822)	(5.795)	(5.852)	(5.799)
ATT3=1 & ATT5=1	49.014	49.014	48.856	50.248	49.604	48.608	50.607	48.759
	(7.209)	(7.209)	(7.204)	(7.248)	(7.227)	(7.197)	(7.260)	(7.201)
Losses due to negative effect(s) of erosion control to prevent 10 feet of erosion								
ATT1 (=1, visible structure)	20.749	20.749	19.545	30.645	25.363	17.684	33.702	18.812
	(4.275)	(4.275)	(4.189)	(5.336)	(4.696)	(4.077)	(5.773)	(4.142)
ATT2 (=1, swim danger)	25.549	25.549	24.282	35.958	30.402	22.325	39.173	23.511
	(4.420)	(4.420)	(4.333)	(5.511)	(4.849)	(4.221)	(5.964)	(4.286)
ATT3 (=1, wildlife viewing ↓)	29.326	29.326	28.010	40.138	34.368	25.977	43.479	27.209
	(4.632)	(4.632)	(4.541)	(5.767)	(5.080)	(4.423)	(6.238)	(4.491)
ATT4 (=1, water quality ↓)	15.009	15.009	13.880	24.291	19.337	12.134	27.159	13.192
	(3.988)	(3.988)	(3.908)	(4.983)	(4.382)	(3.804)	(5.393)	(3.864)
ATT5 (=1, sand quality ↓)	27.089	27.089	25.803	37.663	32.020	23.814	40.929	25.020
	(4.731)	(4.731)	(4.641)	(5.843)	(5.172)	(4.522)	(6.301)	(4.591)
ATT1=1 & ATT4=1	32.025	32.025	30.674	43.126	37.201	28.586	46.556	29.852
	(6.141)	(6.141)	(6.056)	(7.159)	(6.545)	(5.943)	(7.581)	(6.009)
ATT3=1 & ATT5=1	57.433	57.433	55.751	71.250	63.876	53.153	75.519	54.728
	(7.589)	(7.589)	(7.491)	(8.792)	(8.063)	(7.362)	(9.299)	(7.437)

Note: Standard errors are in the parentheses. By comparing the benefits and losses in Tables 6 and 8A, the shaded cells indicate the cases where recreation losses of erosion outweigh the losses from the negative effects of erosion control that preventing erosion generates overall positive recreational benefits.

TABLE 8B
Annual Per-Person Losses due to Effects of Erosion Control on Beach Environment ($)
- The Activity Specific Model

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
Losses due to negative effect(s) of erosion control to prevent 1 foot of erosion								
ATT1 (=1, visible structure)	15.363	2.997	10.073	3.211	22.444	12.421	31.996	29.252
	(6.780)	(5.387)	(7.299)	(5.379)	(9.082)	(7.699)	(6.497)	(6.325)
ATT2 (=1, swim danger)	20.472	14.008	20.648	21.100	20.996	18.965	22.791	19.150
	(4.237)	(4.736)	(4.259)	(4.245)	(4.258)	(4.172)	(4.410)	(4.176)
ATT3 (=1, wildlife viewing ↓)	24.473	24.544	16.184	21.601	28.118	27.426	22.585	27.104
	(4.450)	(4.453)	(4.576)	(4.425)	(4.666)	(4.647)	(4.428)	(4.615)
ATT4 (=1, water quality ↓)	6.896	5.092	28.414	5.644	25.359	1.734	7.285	4.604
	(4.049)	(4.059)	(8.351)	(4.206)	(8.276)	(3.835)	(4.106)	(3.883)
ATT5 (=1, sand quality ↓)	14.849	3.921	12.152	15.288	13.881	21.358	19.487	18.199
	(4.232)	(4.153)	(4.139)	(4.324)	(4.508)	(4.514)	(4.413)	(4.334)
ATT1=1 & ATT4=1	23.133	7.797	41.880	7.913	54.407	14.156	40.560	35.245
	(8.064)	(6.390)	(10.828)	(6.394)	(13.201)	(8.752)	(8.451)	(8.100)
ATT3=1 & ATT5=1	43.651	29.166	30.540	39.815	46.198	56.493	46.135	51.612
	(7.026)	(6.579)	(6.749)	(6.950)	(7.603)	(7.910)	(7.223)	(7.528)
Losses due to negative effect(s) of erosion control to prevent 10 feet of erosion								
ATT1 (=1, visible structure)	20.457	7.368	14.001	13.956	31.702	15.093	49.540	33.454
	(7.240)	(5.759)	(7.713)	(6.616)	(10.100)	(7.912)	(8.192)	(6.523)
ATT2 (=1, swim danger)	25.864	19.023	25.083	34.407	30.112	21.844	38.780	22.932
	(4.499)	(5.058)	(4.448)	(5.490)	(4.899)	(4.273)	(6.071)	(4.329)
ATT3 (=1, wildlife viewing ↓)	30.098	30.174	20.405	34.980	37.934	30.574	38.539	31.217
	(4.743)	(4.746)	(4.793)	(5.711)	(5.393)	(4.767)	(6.148)	(4.793)
ATT4 (=1, water quality ↓)	11.494	9.585	33.221	16.738	34.903	4.067	20.654	7.782
	(4.298)	(4.301)	(8.799)	(5.240)	(9.357)	(3.933)	(5.516)	(4.030)
ATT5 (=1, sand quality ↓)	19.913	8.346	16.179	27.763	22.298	24.314	34.917	21.941
	(4.528)	(4.425)	(4.353)	(5.593)	(5.135)	(4.629)	(6.125)	(4.503)
ATT1=1 & ATT4=1	28.680	12.449	47.332	19.332	66.804	16.883	59.552	39.697
	(8.503)	(6.730)	(11.398)	(7.530)	(14.610)	(8.963)	(10.026)	(8.295)
ATT3=1 & ATT5=1	50.397	35.066	35.449	55.802	57.789	60.564	66.069	56.743
	(7.330)	(6.874)	(6.982)	(8.261)	(8.300)	(8.034)	(9.000)	(7.708)

Note: Standard errors are in the parentheses. By comparing the benefits and losses in Tables 6 and 8B, the shaded cells indicate the cases where recreation losses of erosion outweigh the losses from the negative effects of erosion control that preventing erosion generates overall positive recreational benefits.

Appendix A. Sample Conjoint-Contingent Behavior Questions in the Survey

Suppose that this beach were to erode by 1 foot next year if no erosion controls were undertaken. Would this affect the number of trips you take to this beach next year?

1. YES 2. NO

How would this affect the number of trips you take to this beach next year?

1. Take fewer trips ⇒ How many fewer? _____ FEWER TRIPS
2. Take more trips ⇒ How many more? _____ MORE TRIPS

As you have seen in the booklet and the impact information sheet, erosion control programs can help prevent erosion but at the same time they can also result in other impacts on the beach environment.

Suppose by the end of this year an erosion control program (Program A) were implemented at this beach to prevent the 1 foot of erosion from occurring. However, this erosion control program would also result in the following impacts on the beach environment at this beach.

Program A
Impact:
1. Beach aesthetics: Visible structure/device installed
2. Swimmer impact: No danger to swimmers
3. Wildlife viewing: 50% less
4. Salt water quality: No change
5. Sand quality: Coarser sand with small rocks

Given the implementation of this erosion control program and its impacts, would it affect your trip decision(s) to this beach next year?

1. YES 2. NO→ (**Skip to B_9**)

How would the implementation of this erosion control program affect the number of trips you take to this beach next year?

1. Take fewer trips ⇒ How many fewer? _____ FEWER TRIPS
2. Take more trips ⇒ How many more? _____ MORE TRIPS

Effects of Wetland Proximity and Type on
Market Prices and Individual Choices of Residential Housing

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Abstract

Wetland ecosystems have long been recognized as serving important biological and economic functions. This study investigates specific economic effects of wetlands, namely the role that proximity to wetlands plays in residential housing markets. Using hedonic property price and discrete housing choice analyses, we find that proximity to wetlands in three counties in central Florida can either positively or negatively impact the prices of surrounding residential properties and the probability of choosing properties to purchase. Whether proximity has positive or negative amenity effects on market prices and individual choices is shown to be dependent upon the definition of a wetland and whether or not the wetland is protected from future development.

Effects of Wetland Proximity and Type on
Market Prices and Individual Choices of Residential Housing

I. Introduction

The overall goal of the project "A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods" (EPA STAR Grant RD-83159801-0) is to develop and test a consistent framework to estimate the value of wetland services given that the diverse nature of wetland services undermines their complete valuation through a single method or data source. Our approach employs a joint modeling strategy to integrate revealed preferences (RP) from a discrete choice model of a housing market and stated preferences (SP) from a pairwise choice survey based upon public land acquisition. There are four interrelated objectives to the project: 1) To estimate the demand for proximity to wetlands and other water resources using discrete choice and hedonic property price models; 2) to estimate the demand for ecosystem services from different types of wetlands using a stated choice survey; 3) to develop and test a combined discrete choice model from the RP and SP data to produce a general valuation function for wetland ecosystem services; and 4) to estimate the implicit prices of wetland services in wetland mitigation banking markets.

This paper documents the data collection and construction aspect and reports estimation results specific to objective 1 of the project. Of interest is the effect of proximity to wetlands on the market prices and individual choices of residential housing. We investigate these effects across Orange, Volusia, and Polk counties in central Florida. In addition to the cross-county comparisons, we examine the sensitivity of the models to alternative definitions of wetlands. Specifically, wetlands are defined at various levels of aggregation, ranging from simply the

nearest wetland to specific types of forested and non-forested wetlands. As central Florida wetlands also vary legally in terms of their ownership and potential to be converted into developed lands in the future, we also investigate the effects of their 'protection' status. The findings indicate significant amenity and disamenity effects of proximity to wetlands within each county and between counties and that the sign, magnitudes, and significance of the effects are sensitive to how wetland proximity is defined.

II. Background

A key aspect of both the revealed preference analysis reported in this paper and the stated preference land acquisition survey currently in the field is the use of GIS to identify, classify, and measure the composition of wetlands and alternative land uses within the landscape. For the revealed preference analysis, this information is integrated with property sales data obtained from the county tax appraisers. This section of the paper documents the approach and assumptions used for the construction of the spatial landscape variables and present summary statistics on the integrated datasets across the three county study region.

To begin, digital land cover/use maps were acquired from the two regional water management districts with jurisdiction in the respective counties (St. John's River Water Management District (SJRWMD) for Orange and Volusia counties; Southwest Florida Water Management District (SFWMD) for Polk county). These maps include data based on medium and low altitude flight imagery collected in 2000 and 2003 at scales of 1:24,000 and 1:6,000 resulting in an image resolution of 1 meter. The data were analyzed and interpreted into cover and land use types by the water management districts based on the Florida Land Use and Cover

Classification System (FLUCCS). The FLUCCS classifies hundreds of land types and includes more than 25 types of wetlands. These data are more accurate than the National Wetland Inventory produced by the U.S. Fish and Wildlife Service because the water management districts use the most recent flight imagery and the images are interpreted by local specialists.

The composition of the landscape in the three counties was aggregated into 6 mutually exclusive categories. These include: (1) residential land; (2) commercial and industrial land (including transportation, and utilities); (3) agriculture and rangeland (cropland, pasture, groves, dry prairie, brush land, and barren land); (4) upland forests (coniferous and hardwood); (5) water (lakes, rivers, and reservoirs); and (6) freshwater wetlands.

The portion defined as wetlands was divided into four mutually exclusive categories based on the dominant type of vegetation within the wetlands. These include: (1) wetland hardwood forests (loblolly bay, tupelo, and bottomland hardwoods); (2) coniferous forests (cypress, pond pine, and cabbage palm); (3) freshwater marshes (sawgrass, cattail, and other aquatic vegetation); and (4) wet prairies (emergent and sparse vegetation). The first two categories are distinguished by tree cover and crown closure whereas the latter categories are open habitats with short or no vegetation. These categories are consistent with prior hedonic pricing analyses of wetland values.

The composition of the landscape comprising the study area is summarized in Table 1. The data reveal sizable differences in the composition of the landscape within a given county and across the three counties. However, in each county about fifteen percent of the landscape is comprised of wetlands (17.9% in Orange county; 16.7% in Volusia county; 13.9% in Polk county). Considering the wetland categories, Orange and Volusia counties have comparable

percentages of coverage in all cases, though Volusia county has about 30,000 more wetland acres than Orange county. For these counties, wetland hardwood forests and wetland coniferous forests are the dominant wetland types, comprising more than 70% of the total acreage defined as wetlands. Similar to Orange and Volusia counties, more than 70% of the total wetland acreage in Polk county is attributed to wetland hardwood forests and coniferous forests, with about 50% of the total acreage defined as wetland coniferous forest.

The property sales data used in the hedonic price and discrete housing choice analyses spans the three county study area over the period January 2000-December 2004. The data were obtained from the county tax appraisers, and all unqualified sales and other sales that did not appear to be arm's-length transactions were discarded in constructing the datasets. In addition to identifying the sales prices of single-family residential properties, dates of sale, and geographic locations, the data contains a variety of physical property attributes commonly included in property value analyses. For this study, a set of property attributes that were common and directly comparable between the counties are included in the datasets. These include the number of bedrooms and bathrooms; the square footage of the structure under central air/heating, the square footage of the land (or parcel); the age of the home; and the presence of a pool.

For generation of the spatial/environmental variables to include in the hedonic and discrete choice models, the property sales data were overlaid with GIS land use maps and maps identifying a variety of natural and human-made spatial attributes. Using mapping tools in ArcInfo 9.0, single family residential property sales were geo-located. The Euclidean distances between the centroid of each parcel and the edge of each of the nearest of the four types of

wetlands and to other natural amenities (e.g., lakes and upland forests) were measured. In addition, the sizes of these nearest natural amenities were also measured.

The econometric analysis focused initially upon the hedonic property price model. Preliminary estimates of alternative specifications of the hedonic models revealed some counter-intuitive results, which lead to concern about possible mis-measurement of the distance and size (area) variables. To investigate, we selected a sample of properties to test for consistency in the distance calculations and identification of the correct land use. It was discovered that several factors could be attributed to potential mis-measurement of the variables. These included the temporal lags between the land use maps and the date property sales, the measurement of the centroids of the parcels, and inconsistencies between the GIS land use maps obtained from the water management districts and the county property appraiser tax rolls. The lags between the creation of the land use maps by the state water management districts relative to the continuous urban and rural developments in the three counties were believed in some cases to result in the identification of upland forests and wetlands within the landscape that no longer existed due to residential and commercial development.

Other measurement concerns arose because the county property appraisers and the water management districts categorize land uses differently, and the land use maps differed with respect to their distinctions between developed and undeveloped lands. This is noteworthy because identifying the location of the centroid of residential parcels is a necessary first step for calculating the distances between the parcels and the desired environmental attributes. As an example, it was found that in many cases the legal boundaries of lakefront parcels extended into their associated lakes, in which case the measured centroid of the parcels could be within the

lakes. When the distances to the nearest lakes were measured for these parcels, rather than identifying the properties as being adjacent to lakes (i.e., lakefront), the GIS software would measure the distance to the next nearest lake. This was especially problematic with large lakes due both to the large number of parcels that surrounded such lakes and because the nearest of the other environmental amenities could be mis-identified, in which case the distances to these amenities was necessarily mis-measured.

To correct for this issue, the initial land-use maps were reconstructed. To begin, portions of Orange county were updated with land-use maps that were not available when the datasets were initially constructed. Next, all parcels that the assessor's office had identified as being residential, commercial, or industrial property were dissolved into a single land mass that was then removed from the land-use maps that identified upland forests and wetland areas. As a result, the total area identified as being forest or wetlands was reduced. Lastly, the boundaries of those lakefront properties that were identified as extending into the water were redefined by excluding the submerged portions of the parcels, and the centroids of the parcels were then redefined for the distance calculations.

An issue that arose in the process of reconstructing the land-use maps concerned the fragmentation of the undeveloped segments of the landscape. After dissolving and removing the residential, commercial, industrial land uses as discussed above, it was found that in many cases there were small portions of wetlands that were contained in the remaining area. These slivers were sufficiently small so as not to be identifiable with the naked eye in the aerial photos and were identified as being associated with both residential and commercial property development (i.e., small pieces of wetlands were contained between two or more developed parcels).

In developing a criterion to apply on a county-wide scale to distinguish these areas from other undeveloped areas, we found that the borders of the slivers were consistently defined by straight lines, whereas the borders of natural areas (wetlands and upland forests) tended to be curvilinear. Consequently, the ratio of edge length to interior area was considerably larger for the non-natural patches than for natural patches. GIS reference books document similar metrics that have been constructed for measuring habitat fragmentation and other ecological indicators.[1] One fragmentation index is the ratio of the patch perimeter to the patch area, which reflects the extent to which human dominated, regular shapes "fracture" otherwise continuous land cover areas.

Comparing the perimeter-to-area ratios between developed and natural environments revealed that patches of upland forests in Orange county that had ratios exceeding 0.04 were typically developed, while large and intact undeveloped patches consistently had ratios as small as 0.0015. By comparison, subdivisions and developed patches tended to have much larger ratios. Further, the perimeter-to-area ratios were found to vary between upland forests and the four wetland categories. Patches of upland forest tended to have very small ratios, (less than 0.04), whereas wetland prairies tended to have more 'feathery' shapes–with long perimeters and narrow interiors–resulting in perimeter-to-area ratios approaching 0.15. These differences were also true between counties. In Volusia county, which has many coastal areas and more topographical variation than Orange and Polk counties, the perimeter-to-area ratios tended to be greater than those ratios calculated in Orange and Polk counties.

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[1] See, for example, Stan Morain (Ed.). *GIS Solutions in Natural Resources Management*. Santa Fe: OnWord Press, 1998.

After completing this step of reconstructing the land-use maps, the upland forest and wetland areas were redrawn as new shapes in GIS and then cast into a new land use aggregation map. The areas and perimeters of the patches were then re-measured and the distances between the various land types and the residential parcels were re-calculated for inclusion in the hedonic price and discrete housing choice analyses.

In addition to the distance and area calculations, the composition of the land surrounding the residential parcels was measured from the revised land-use maps. This process entailed aggregating the land-types within the landscape into residential lands, commercial/industrial lands, agricultural lands, and undeveloped lands and waters. The size of the surrounding 'buffer' areas is defined as one square mile. To create the land-use buffers, we first attempted to create parcel-specific buffers (i.e., a buffer around each individual parcel) and then overlay the land-use maps so as to identify the composition of land-uses within each buffer. Despite the available computer power, this process proved to be computationally burdensome, given that the three-county datasets contain approximately 120,000 residential properties.

A second approach that was investigated entailed aggregated the landscape into two land-types: developed and undeveloped lands; however, the computational process remained problematic. The final approach that was investigated, and that which was adopted in this study, employed CADD (drafting) software to partition the counties into grids spanning one square-mile square. ArcGIS was then used to aggregate the landscape into four land-uses: residential lands, commercial/industrial lands, agricultural lands, and undeveloped lands and water. The percentage of each land-type contained in the square-mile grids were then calculated. The residential parcel map was then overlaid with the land-use grid so as to link the land-uses within

the grids to the individual parcels. With this step, the final residential property datasets were complete, and estimation of the hedonic price and discrete housing choice models could proceed.

Table 2 reports summary statistics for the variables included in the revealed preference hedonic and discrete choice analyses. The data indicate that the average sales price (expressed in 2000 dollars) in Orange county is about $40,000 greater than in Volusia county, and about $60,000 greater than Polk county. The average heated area of the home is comparable between the counties; however, the average parcel area is notably smaller in Orange county relative to Volusia and Polk counties.

Considering the wetland characteristics, the distance to the nearest of each of the four wetlands categories exceeds 1000 meters on average. In all cases the average size of the nearest wetland hardwood forest and wetland coniferous forest exceeds 100,000 square meters. However, there is considerable variation in the sizes of the individual wetland parcels as indicated by the relative size of the respective standard deviations. In contrast, the average sizes of the nearest wetland marsh and wetland prairies are relative small, though considerable variation in the sizes of the parcels is again indicated by the respective standard deviations.

Table also reports the portions of wetlands that are designated as being protected from development. Protected wetlands in central Florida appear in two forms. First, wetlands contained in the Florida Natural Areas Inventory (FNAI) are designated as being regionally significant, are publicly owned, and are not subject to development in the future. In addition, other protected wetland areas were identified within the counties by land use codes that were designated as being set aside by developers and owned by neighborhood homeowner associations; these include conservation easements, undeveloped lands, and open spaces not

available for future development. The portion of the number of protected wetlands varies within the counties by wetland type and across the counties for each wetland type. The values range from a minimum of 2.2 percent of wetland coniferous forest in Orange county to a maximum of 32.5 percent of wetland prairie in Volusia county.

Lastly, table 2 reports on the average composition of the land surrounding the residential properties that sold over the period. In all cases, the majority of the land contained in the square mile grid placed around the properties is developed and in residential use. About 20% of the surrounding land in all cases is defined as recreational, and the remainder is agricultural use.

III. Hedonic Property Price and Residential Housing Choice Analyses

The property sales data integrated with the land composition data is used to measure the amenity effects of proximity to wetlands. First, the effect of wetland proximity is investigated with respect to the sales prices of residential properties using hedonic price analysis. This approach defines a property as a bundle of physical characteristics located within a landscape, and which can be purchased in a competitive market, and then models the variation in property prices as a function of these physical and spatial attributes. Second, we estimate random utility models of individual housing choice in order to isolate the effect of wetland proximity on individual preferences (i.e., the parameters of an individual's indirect utility function). This approach has a long-standing history in modeling location choice and destination choice and is applied here to housing choice as a function of property attributes and spatially variant socioeconomic and environmental attributes. In both cases, the independent variables include those reported in table 2. For brevity, we do not detail here the technical aspects of the hedonic

and discrete choice models; interested readers are referred to Haab and McConnell (2002) for technical details.[2]

In the proceeding analyses, the effects of proximity to wetlands is estimated for unprotected wetlands and the two categories of protected wetlands discussed above. To test for interactive effects of proximity to a given type of wetland (e.g., wetland hardwood forests), the respective distance variable is interacted with (i.e., multiplied by) the area of the wetland and with dummy variables identifying whether the respective wetland is a publicly protected wetland (FNAI Protected) or is informally protected through, for example, an easement or collective ownership by a neighborhood organization (Other Protected).

In addition, we examine the effect of wetland proximity under three definitions of a nearest wetlands; these differ in terms of their level of aggregation. The first wetland variable definition, referenced in the tables below by Nearest Wetland, includes that wetland which is nearest to a property, with no distinction made to its type (e.g., wetland coniferous forests vs. wetland marshes or prairies). The second wetland definition distinguishes between forested and non-forested wetlands and is referenced below by Nearest Forested Wetland and Nearest Non-forested Wetland. Thus, with this definition, there are two wetland distance variables, two wetland area variables, and four protection status dummy variables. The third wetland definition disaggregates the forested and non-forested wetlands into, respectively, wetland hardwood and wetland coniferous forests and wetland freshwater marshes and wetland prairies. These are

[2] Timothy C. Haab and Kenneth E. McConnell, *Valuing Environmental and Natural Resources*. Cheltenham, UK: Edward Elgar Publishing Limited, 2002.

referenced below by their respective names (e.g., Nearest Wetland Prairie). Thus, there are four wetland distance variables, four area variables, and eight protection status dummy variables.

Hedonic Property Price Analysis

To proceed with the hedonic property price analysis an assumption must be made about the econometric specification of the hedonic price equation. To accommodate possible non-linearities between property prices and the continuous independent variables (e.g., the square footage of the home and its distance to a wetland), we use the commonly employed double-log specification, whereby the dependent and continuous independent variables are converted to natural logarithms.

Table 3 presents the estimation results specific to the wetland distance variables (the full set of estimation results is available in an appendix). For the specification that includes only the nearest wetland (Model 1) the results suggest that across all three counties the distance to wetlands is positively related to property prices on average as gauged by the positive and statistically significant coefficients on the bulk of the variables. Furthermore, the positive and significant coefficients on the protection status interactions indicate even larger positive effects on the mean property price as distance increases. One should be cautious, however, in considering the results with this specification of the model. Specifically, the results from model 2 reveal the aggregation problems embedded in model 1. For example, in Orange county the results from this second specification suggest that property prices increase on average as the distance to the nearest forested wetland decreases but that the mean price decreases in the case of non-forested wetlands. In contrast, the results for Volusia and Polk counties suggest that

residential property prices tend to increase on average as distance increases for both forested and non-forested wetlands as gauged by the large number of positive and significant coefficients.

Aggregation effects also appear to be present in model 2 as indicated by the estimation results from model 3, which identifies the specific types of forested and non-forested wetlands. Similar to model 2, mean property prices are found to be negatively related to the distance to the nearest forested wetlands and positively related to the distance to non-forested wetlands. However, as the magnitudes of the coefficients differ by wetland type, the effects of wetland proximity on property prices are unique to each wetland type. Note, however, that although the estimation results differ between the three model specifications, the overall fit of the models is largely unaffected by the choice of wetland variables as gauged by the invariance of the adjusted R^2 statistics.

The primary interest in table 3 regards the signs, magnitudes, and significance of the coefficients. In addition, the estimation results may be used to calculate the implicit prices of distance (i.e., the marginal effects of distance) across the different types of wetlands and protection status categories within each county. These are reported in Table 4. As the distance variables are measured in meters, the implicit prices are interpreted as the change in the mean property price for a one meter change in distance to the nearest wetland of a given type. A negative sign indicates that distance is an amenity, with the property price increasing on average as the distance to the wetland decreases, and a positive sign indicates that distance is a disamenity. The results for the Nearest Wetland (model 1) specification indicate that wetland proximity is a disamenity in all three counties regardless of the protection status. Furthermore, the disamenity effect is larger for protected wetlands than unprotected wetlands.

However, similar to the results in Table 3, the aggregation effects resulting under the Nearest Wetland specification is revealed by the partially disaggregated (model 2) and fully disaggregated (model 3) specifications. For example, in Orange county the results for model 2 indicate that proximity to forested wetlands is an amenity, while non-forested wetlands have a disamenity effect on the mean property price. Relative to unprotected forested wetlands, the amenity effect is larger for FNAI-Protected wetlands and smaller for Other-Protected wetlands. Alternatively, relative to unprotected non-forested wetlands, the disamenity effect does not differ with FNAI-Protected wetlands but is significantly larger with other-protected wetlands. The amenity effect is differentiated between the specific types of forested and nonforested wetlands in model 3. In Orange county, proximity to wetland hardwood and wetland coniferous forests has small amenity effects, while proximity to non-forested wetlands has relatively large disamenity effects, most notably with freshwater wetland marshes. In contrast to Orange county, the only amenity effect that is identified in Volusia county is associated with wetland hardwood forests, while proximity to wetlands in Polk county is found to be a disamenity for all wetland definitions and categories of protection status.

Having examined the effects of wetland proximity on the market prices of residential properties, we turn next to the analysis of individual property choice. Here, we control for property prices and isolate the effect of proximity to the various categories of wetlands on housing choice. Assuming home buyers are utility maximizers, the property choice analysis may be used to measure individual preferences (i.e., marginal utilities) for proximity to the various categories of wetlands.

Discrete Housing Choice Analysis

To proceed with the random utility analysis of individual housing choice, two fundamental assumptions must be made. The first regards the specific form of discrete choice model to estimate. For this analysis, the conditional logit model is employed. The second necessary assumption regards the definition of the choice set (i.e., the set of alternative properties) from which an individual selects a property to purchase. In some applications (for example, survey based recreational site choice analysis), the researcher has individual-specific information that can aid in specifying choice sets.

However, with property choice analyses, and as recognized by others, very limited individual information is typically available; the present application is no exception. As such, we use the random draws approach to choice set generation, whereby an individual's choice set is defined by the chosen property and a set of alternative properties that is randomly drawn from all properties purchased within a temporal window around the sale date of the chosen property, similar to Banzaf and Smith (2007).[3] We define this window as the three-month period around the sale date (for example, if the property was purchased in April, the three-month period includes March, April, and May). For each home buyer we randomly draw 249 properties from all properties sold within this period; thus, each choice set is unique and contains 250 properties.

The sample of individuals used in the analysis is defined as those homeowners identified in the tax appraiser data as receiving a 'homestead exemption' on their property taxes. In Florida the exemption is assigned to a property if it is owned by a Florida resident who uses the property

[3] H. Spencer Banzaf and V. Kerry Smith (2007), "Meta Analysis in Model Implementation: Choice Sets and the Valuation of Air Quality Improvements," forthcoming in *Journal of Applied Econometrics*.

as their primary residence. By defining the sample of home buyers in this way, we exclude nonresidents and individuals, partnerships, and corporations that purchase properties solely for investment purposes, and whose preferences may differ from those whose properties serve as their primary residence. This definition of the sample is also consistent with that employed in the stated preference wetland valuation survey referenced in the introduction (see objective 2).

Table 5 reports the conditional logit estimation results by county for the three specifications of the wetland variables (the full set of estimation results is available in an appendix upon request). In each case, the coefficient estimates on the distance and distance interaction variables, their standard errors, and significance levels are reported. In addtion, and similar to using the estimated hedonic models to calculate the implicit price of distance to a wetland, the estimated discrete choice models may be used to calculate the marginal utility of distance to gauge whether wetland proximity has amenity or disamenity effects on individual utility. For each of the three specifications of the model, Table 6 reports these estimated marginal utilities and their significance as gauged from the significance of the individual parameter estimates.

Considering the results reported in Table 5 and Table 6, the Nearest Wetland specification (model 1) indicates no significant difference between the effect of distance to unprotected and FNAI Protected wetlands in Orange county, and that the effect of distance appears solely through the area interaction variable. Further proximity to wetlands designated as Other Protected has amenity effects that differ significantly from those of the other two protection status categories. The results in Volusia county indicate significant amenity effects of

distance to unprotected and Other Protected wetlands and significant disamenity effects with FNAI Protected wetlands, while distance has no significant effect in any case in Polk County. However, as with the hedonic price analysis, the aggregation effects of the Nearest Wetland specification are revealed by model 2 and model 3. Across all three counties proximity to forested wetlands has significant amenity effects for unprotected wetlands and for Other Protected wetlands in Orange county, while proximity to FNAI Protected wetlands has significant disamenity effects in Orange and Volusia counties. For non-forested wetlands in Volusia county there is no significant amenity effect for proximity to unprotected wetlands, but as with forested wetlands, proximity to FNAI Protected wetlands has significant disamenity effects. The results for forested wetlands in Polk county indicate amenity effects that do not differ significantly between protection status categories. Alternatively, the results from non-forested wetlands indicate disamenity effects that do not differ significantly by protection status.

Looking next at the wetlands within the forested and non-forested categories (model 3), the results indicate significant amenity effects for unprotected and Other Protected wetland hardwood forests and unprotected wetland coniferous forests, while proximity to FNAI Protected wetlands has disamenity effects for both types of forested wetlands in Orange county. In Volusia county, the only significant result is an amenity effect for wetland hardwood forests designated as Other Protected. And in Polk county the results indicate large and significant amenity effects for all protection status categories of wetland hardwood forests and significant disamenity effects of proximity to wetland coniferous forests in all cases.

Lastly, considering the specific types of non-forested wetlands, proximity to unprotected wetland marshes has large and significant disamenity effects in Orange county and significant

amenity effects in Volusia and Polk counties. Again, amenity effects are associated with the Other Protected designation in the case of freshwater marsh in Orange county and disamenity effects in Volusia county. And proximity to unprotected wetland prairies has significant amenity effects in Orange and Polk counties, while the signs of the significant protection status interactions indicate both amenity and disamenity effects across the counties.

To summarize, the findings indicate significant amenity and disamenity effects of proximity to wetlands within each county and between counties. However, the sign, magnitudes, and significance of the effects are sensitive to how wetland proximity is defined.

IV. Conclusions

Wetland ecosystems have long been recognized as serving important biological and economic functions. This study investigated specific economic effects of wetlands, namely the role that proximity to wetlands plays in residential housing markets. Using hedonic property price analysis, we found that proximity to central Florida wetlands can either positively or negatively impact the prices of surrounding residential properties. Whether proximity has positive or negative amenity effects on property prices was shown to be dependent upon the definition of a wetland and whether or not the wetland was protected from future development. Similar conclusions about the amenity effects of proximity to wetlands were drawn from the random utility model of individual housing choice controlling for property prices.

A natural extension of the present study is to use the estimated hedonic and discrete choice models to measure the nonmarket values attached to wetlands in the study area. In the context of the property price analysis, and given that the housing markets are arguably unique to

each of the three counties, the second stage of the hedonic model could be estimated in order to obtain the demand equation relating property prices to distance and estimate the consumer surplus associated with wetland proximity across the various wetland type and protection status categories. Alternatively, the discrete choice model may be used to estimate individual willingness to pay for changes in various attributes of the wetlands. Complementary to the hedonic analysis, this could entail calculating the value of proximity, but can also include valuing the loss of unprotected wetlands to development or changes in the protection status of the specific types of wetlands.

Table 1. Total Land Use Composition and Wetland Composition by Central Florida County in 2005

	Orange County		Volusia County		Polk County	
Description	Area (Hectares)	% Land Cover	Area (Hectares)	% Land Cover	Area (Hectares)	% Land Cover
All Land Types						
Residential	68,099	26.8	45,992	10.3	66,673	20.1
Commercial and Industrial	55,094	21.7	116,190	26.0	86,962	26.3
Agriculture and Rangeland	45,612	18.0	134,873	30.2	52,208	15.8
Water	24,309	9.6	31,330	7.0	41,076	12.4
Upland Forest	15,435	6.1	43,921	9.8	38,313	11.6
Wetlands	45,483	17.9	74,517	16.7	45,996	13.9
Total Area	254,031	100.0	446,823	100.0	331,228	100.0
Wetland Composition						
Wetland Hardwood Forest	15,754	34.6	25,508	34.2	10,303	22.4
Wetland Coniferous Forest	18,044	39.7	27,511	36.9	23,616	51.3
Wetland Freshwater Marsh	6,821	15.0	13,842	18.6	3,431	7.5
Wetland Prairie	4,864	10.7	7,656	10.3	8,646	18.8
Total Wetlands Area	45,483	100.0	74,517	100.0	45,996	100.0

Table 2. Summary Statistics on Samples of Central Florida Residential Housing Sales, January 2000-December 2004

		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Variable Description	Unit	Mean	Std Deviation	Mean	Std Deviation	Mean	Std Deviation
Property Characteristics							
Sales Price	2000 Dollars	173,785.60	151,625.70	134,361.40	80,317.46	115,455.10	70,952.82
Heated Area	$Feet^2$	1,813.55	746.27	1,682.71	565.50	1,630.87	608.75
Area of Parcel	$Feet^2$	11,699.95	18,511.56	19,126.90	41,457.09	18,231.50	44,644.88
Number of Bedrooms	--	3.29	0.74	2.92	0.61	2.90	0.56
Number of Bathrooms	--	2.15	0.68	2.02	0.50	1.85	0.59
Home Age	Years	17.04	13.09	19.97	15.12	25.92	20.48
% With Pool	--	0.24	--	22.95	--	21.64	--
% In Flood Zone	--	0.04	--	8.88	--	3.31	--
Locational/Spatial Characteristics							
Nearest Wetland Hardwood Forest: Distance	Meters	1,554.15	1,273.64	2,226.90	1,662.21	1,128.49	890.64
Area	$Meters^2$	307,792.90	1,927,734	181,448.10	374,925.00	245,917.9	882,989.70
% Protected	--	29.39	--	30.90	--	14.97	--
Nearest Wetland Coniferous Forest: Distance	Meters	1,303.41	1,119.03	1,670.15	1,061.82	1,794.20	1,183.91
Area	$Meters^2$	96,383.88	519,952	334,626.30	1,579,265	183,072.70	640,792.90
% Protected	--	2.21	--	22.68	--	22.25	--

Variable Description		Unit	Orange County (N = 76,933) Mean	Orange County (N = 76,933) Std Deviation	Volusia County (N = 30,249) Mean	Volusia County (N = 30,249) Std Deviation	Polk County (N = 19,716) Mean	Polk County (N = 19,716) Std Deviation
Nearest Wetland Freshwater Marsh:	Distance	Meters	1,359.60	1,241.12	1,535.66	1,015.61	1,002.93	1,467.88
	Area	Meters^2	14,060.85	24,000.10	15,310.99	41,094.71	27,640.18	84,362.32
	% Protected	--	19.01	--	9.27	--	11.28	--
Nearest Wetland Prairie:	Distance	Meters	1,133.10	800.74	1,166.62	687.84	1,076.05	773.01
	Area	Meters^2	18,030.85	26,887.24	20,491.71	41,353.43	30,044.61	174,951.00
	% Protected	--	32.49	--	9.49	--	5.48	--
Nearest Upland Forest:	Distance	Meters	1,266.21	1,046.11	1,597.71	1,000.42	989.75	654.65
	Area	Meters^2	124,814.50	408,266.80	1,612,130	3,978,746	93,661.45	195,949.30
	% Protected	--	23.15	--	52.80	--	13.13	--
Nearest Named Lake:	Distance	Meters	1,393.97	1,685.89	2,951.05	3,150.26	1,205.74	1,330.71
	Area	Meters^2	269.15	1,803.15	230,542.10	3,081,701	1,670,160	3,849,551
Nearest Other Water:	Distance	Meters	2,669.52	1,887.94	658.14	587.80	4,647.43	3,081.40
	Area	Meters^2	4,331.81	7,464.53	728,525.80	3,007,783	26,182.72	48,814.96
Central Business District:	Distance	Meters	13,183.94	5,982.58	25,848	14,323.75	53,395.70	44,337.53
Surrounding Land:	% Residential	--	48.77	--	63.48	--	37.94	--
	% Commercial/Industrial	--	27.36	--	14.89	--	18.27	--
	% Recreational	--	18.62	--	18.60	--	18.35	--
	% Agricultural	--	5.24	--	3.03	--	25.43	--
Latitudinal Coordinate		Degrees	0.53	0.04	0.61	0.04	0.71	0.05
Longitudinal Coordinate		Degrees	1.53	0.031	1.71	0.05	1.35	0.04

		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Variable Description	Unit	Mean	Std Deviation	Mean	Std Deviation	Mean	Std Deviation
Neighborhood Characteristics							
% of Population Caucasian	--	74.53	--	90.02	--	83.97	--
% of Population Black	--	12.54	--	5.03	--	9.33	--
% of Population Over 65 Years of Age	--	9.89	--	20.28	--	18.26	--
Median Household Income	2000 Dollars	52,237.78	18,038.46	41,266.18	10,015.86	42,023.18	12,089.82
Distribution of Sales by Year							
% of Sales in 2000	--	16.80	--	15.55	--	10.46	--
% of Sales in 2001	--	17.82	--	16.31	--	14.42	--
% of Sales in 2002	--	18.81	--	19.41	--	16.95	--
% of Sales in 2003	--	21.58	--	23.06	--	23.41	--
% of Sales in 2004	--	25.00	--	25.67	--	34.76	--

Table 3. Selected Estimates of Hedonic Property Price Models by County

		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Dependent Variable: Natural Logarithm of Sales Price		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 1:							
Nearest Wetland:	Ln(Distance)	0.002	0.001	0.020**	0.002	0.034**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.0002*	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.005**	0.001	0.009**	0.001	0.003	0.002
	Ln(Distance) x Other Protected	0.004**	0.0003	0.007**	0.001	0.008**	0.001
		Adjusted R^2 = 0.85		Adjusted R^2 = 0.83		Adjusted R^2 = 0.78	
Model 2:							
Nearest Forested Wetland:	Ln(Distance)	-0.019**	0.001	0.002	0.002	0.023**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	0.0004**	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.002*	0.001	0.002**	0.001	0.0005	0.001
	Ln(Distance) x Other Protected	0.001**	0.0004	0.0002	0.0004	0.007**	0.001
Nearest Non-Forested Wetland:	Ln(Distance)	0.011**	0.001	0.024**	0.002	0.028**	0.003
	Ln(Distance) x Ln(Area)	0.002**	0.0001	-0.0003*	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.001	0.001	0.003**	0.001	0.003	0.002
	Ln(Distance) x Other Protected	0.003**	0.0003	0.009**	0.001	0.003**	0.001
		Adjusted ^{2} = 0.85		Adjusted R^2 = 0.83		Adjusted R^2 = 0.78	

Table 3 Continued

Dependent Variable: Natural Logarithm of Sales Price		Orange County (N = 76,933) Coefficient	Orange County (N = 76,933) Standard Error	Volusia County (N = 30,249) Coefficient	Volusia County (N = 30,249) Standard Error	Polk County (N = 19,716) Coefficient	Polk County (N = 19,716) Standard Error
Model 3:							
Nearest Wetland Hardwood Forest:	Ln(Distance)	-0.010**	0.001	-0.030**	0.002	0.021**	0.003
	Ln(Distance) x Ln(Area)	0.0002*	0.0001	0.001**	0.0002	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.002*	0.001	0.001	0.0004	0.001	0.002
	Ln(Distance) x Other Protected	0.004**	0.0003	0.001	0.001	0.005**	0.001
Nearest Wetland Coniferous Forest:	Ln(Distance)	-0.018**	0.001	0.037**	0.002	0.004	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.001**	0.0001	-0.00002	0.0002
	Ln(Distance) x FNAI Protected	-0.006**	0.001	-0.002*	0.001	-0.001	0.002
	Ln(Distance) x Other Protected	---	---	0.0002	0.0004	0.013**	0.001
Nearest Wetland Freshwater Marsh:	Ln(Distance)	0.015**	0.001	-0.001	0.002	0.025**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	0.001**	0.0002	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.002**	0.001	-0.001	0.001	0.0001	0.002
	Ln(Distance) x Other Protected	-0.003**	0.0003	-0.003**	0.001	0.002	0.001
Nearest Wetland Prairie:	Ln(Distance)	0.001	0.001	0.019**	0.002	0.015**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.001**	0.0001	0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.013**	0.001	0.003**	0.001	-0.008**	0.002
	Ln(Distance) x Other Protected	0.002**	0.0002	0.012**	0.001	-0.005**	0.001
		Adjusted R^2 = 0.86		Adjusted R^2 = 0.84		Adjusted R^2 = 0.77	

Note: ** and * indicate significance at the 1% and 5% level, respectively. The full set of estimation results is available in an appendix.

Table 4. The Implicit Price of a 1 Meter Increase in Distance to Wetlands by County

		Orange County	Volusia County	Polk County
Model 1				
Nearest Wetland	Unprotected	$3.92	$2.98	$4.70
	FNAI Protected	5.14	4.48	5.28
	Other Protected	5.12	4.14	6.42
Model 2				
Nearest Forested Wetland	Unprotected	$-0.95	$0.65	$1.79
	FNAI Protected	-1.25	0.86	1.85
	Other Protected	-0.78	0.67	2.75
Nearest Non-Forested Wetland	Unprotected	4.89	2.80	3.88
	FNAI Protected	4.54	3.08	3.97
	Other Protected	5.09	2.82	5.20
Model 3				
Nearest Wetland Hardwood Forest	Unprotected	$-0.83	$-1.13	$0.99
	FNAI Protected	-0.64	-1.09	1.08
	Other Protected	-0.43	-1.09	1.46
Nearest Wetland Coniferous Forest	Unprotected	-0.55	2.16	0.25
	FNAI Protected	-1.34	2.02	0.20
	Other Protected	-0.55	2.18	1.12
Nearest Wetland Freshwater Marsh	Unprotected	3.06	0.31	2.23
	FNAI Protected	2.76	0.22	2.24
	Other Protected	2.68	0.07	2.42
Nearest Wetland Prairie	Unprotected	1.05	1.22	2.47
	FNAI Protected	3.09	1.54	1.60
	Other Protected	1.30	2.62	1.98

Note: Cells are shaded if the corresponding coefficients reported in Table 3 are significant.

Table 5. Conditional Logit Estimates of Residential Housing Choice by County

Dependent Variable: Housing Choice (1/0)		Orange County (I = 34,037)		Volusia County (I = 15,817)		Polk County (I = 10,825)	
Choice Sets: 250 Random Draws from 3 Month Window		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 1:							
Nearest Wetland:	Distance	0.0001	0.012	-0.055**	0.017	0.036	0.032
	Distance x Area	0.004*	0.002	-0.0004	0.001	0.001	0.002
	Distance x FNAI Protected	0.104	0.058	0.101*	0.044	0.093	0.074
	Distance x Other Protected	-0.086**	0.016	-0.280**	0.039	-0.050	0.063
		Pseudo R^2 = 0.02		Pseudo R^2 = 0.004		Pseudo R^2 = 0.03	
Model 2:							
Nearest Forested Wetland:	Distance	-0.052**	0.008	-0.030*	0.012	-0.060**	0.020
	Distance x Area	0.001	0.001	-0.001	0.001	-0.001	0.001
	Distance x FNAI Protected	0.146**	0.025	0.062**	0.019	0.051	0.062
	Distance x Other Protected	-0.077**	0.014	0.024	0.013	-0.014	0.038
Nearest Non-Forested Wetland:	Distance	0.019	0.011	-0.028	0.015	0.059*	0.029
	Distance x Area	0.086**	0.019	-0.005	0.021	-0.038	0.025
	Distance x FNAI Protected	-0.061**	0.037	0.144**	0.028	-0.003	0.102
	Distance x Other Protected	0.002	0.011	-0.174**	0.042	0.044	0.052
		Pseudo R^2 = 0.02		Pseudo R^2 = 0.004		Pseudo R^2 = 0.03	

Table 5 Continued

Dependent Variable: Housing Choice (1/0)		Orange County (I = 34,037))		Volusia County (I = 15,817)		Polk County (I = 10,825)	
Choice Sets: 250 Random Draws from 3 Month Window		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 3:							
Nearest Wetland Hardwood Forest:	Distance	-0.023**	0.006	0.012	0.009	-0.087**	0.016
	Distance x Area	0.0002	0.0002	-0.002	0.001	-0.004**	0.001
	Distance x FNAI Protected	0.060**	0.012	0.010	0.009	0.059	0.054
	Distance x Other Protected	-0.052**	0.009	-0.050*	0.020	-0.014	0.044
Nearest Wetland Coniferous Forest:	Distance	-0.020*	0.009	-0.017	0.012	0.040**	0.011
	Distance x Area	0.0004	0.0006	-0.0004	0.0006	0.008**	0.002
	Distance x FNAI Protected	0.078*	0.031	0.023	0.027	-0.043	0.034
	Distance x Other Protected	---	---	0.008	0.011	-0.002	0.014
Nearest Wetland Freshwater Marsh:	Distance	0.087**	0.009	-0.029*	0.013	-0.068**	0.019
	Distance x Area	0.039*	0.018	-0.006	0.018	0.014	0.021
	Distance x FNAI Protected	-0.027	0.029	0.051**	0.017	-0.180	0.108
	Distance x Other Protected	-0.078**	0.018	0.041*	0.018	0.020	0.042
Nearest Wetland Prairie:	Distance	-0.046**	0.011	0.007	0.016	0.035	0.021
	Distance x Area	-0.012	0.020	0.034	0.019	-0.070**	0.023
	Distance x FNAI Protected	-0.038	0.041	0.085**	0.030	-0.145*	0.068
	Distance x Other Protected	0.052**	0.009	-0.092**	0.031	-0.012	0.045
		Pseudo R^2 = 0.03		Pseudo R^2 = 0.004		Pseudo R^2 = 0.03	

Note: ** and * indicate significance at the 1% and 5% level, respectively. The full set of estimation results is available in an appendix.

Table 6. The Marginal Utility of a 1 Meter Increase in Distance to Wetlands by County

		Orange County	Volusia County	Polk County
Model 1				
Nearest Wetland	Unprotected	0.003	-0.055	0.037
	FNAI Protected	0.108	0.046	0.130
	Other Protected	-0.083	-0.335	-0.013
Model 2				
Nearest Forested Wetland	Unprotected	-0.051	-0.033	-0.062
	FNAI Protected	0.094	0.029	-0.011
	Other Protected	-0.128	-0.010	-0.076
Nearest Non-Forested Wetland	Unprotected	0.031	-0.029	0.048
	FNAI Protected	-0.030	0.115	0.045
	Other Protected	0.033	-0.203	0.092
Model 3				
Nearest Wetland Hardwood Forest	Unprotected	-0.022	0.008	-0.096
	FNAI Protected	0.038	0.019	-0.037
	Other Protected	-0.073	-0.042	-0.110
Nearest Wetland Coniferous Forest	Unprotected	-0.020	-0.018	0.054
	FNAI Protected	0.058	0.005	0.011
	Other Protected	---	-0.011	0.052
Nearest Wetland Freshwater Marsh	Unprotected	0.092	-0.030	-0.064
	FNAI Protected	0.065	0.020	-0.244
	Other Protected	0.014	0.011	-0.044
Nearest Wetland Prairie	Unprotected	-0.048	0.014	-0.014
	FNAI Protected	-0.086	0.100	-0.130
	Other Protected	0.003	-0.077	0.003

Note: Cells are shaded if the corresponding coefficients reported in Table 5 are significant.

Linking Recreation Demand and Willingness to Pay with the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh[1]

June 13, 2007

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Introduction

Economists have use various methods for measuring the economic value of wetlands and results have differed depending on the location and the economic methods. Woodward and Wui (2001) performed a meta-analysis of published U.S. wetlands valuation studies for a number of services including flood control, water quantity and quality, hunting, fishing, wildlife watching, amenities, etc. Only a few studies have considered Great Lakes wetlands, beginning with Jaworski and Raphael's (1978) study of the value of fish, wildlife and recreation of Michigan's coastal wetlands. Several recent studies also address the value of various Midwest wetlands. These include a travel cost analysis for three small hunting sites (van Vuuren and Roy, 1993), a study of the value for commercial fisheries (Amacher, et al, 1989) and a study of Wisconsin wetlands (Mullarkey, 1997). In addition to these, more recent studies look at Michigan residents' willingness to accept different forms of wetlands mitigation (Lupi et al, 2002 and Hoehn et al, 2003).

Whitehead et al (2006) estimate the economic values of Saginaw Bay coastal marshes with multiple methods. Using the site selection travel cost model and conservative aggregation assumptions, an increase in 1125 acres of coastal marsh is valued at about $94,000 annually. The present value is $1.83 million. Willingness to pay for coastal marsh protection is estimated using the contingent valuation method. The annual value of protection of 1125 acres of coastal marsh is $113,000. The present value is $2.2 million.

We find that each acre of coastal marsh is worth $1,627 over a recreational user's lifetime. Over and above the recreational value are the other values estimated with the contingent valuation method. These values add $1,969 per acre over a lifetime. The recreation value and the

willingness to pay value may be combined because analysis of the willingness to pay values indicated that they are not associated with increases in recreation trips. They are entirely nonuse values. The total value of each acre of coastal marsh is, therefore, $3,596 over the lifetime of a resident of the sampled region. The purpose of this paper is to further explore the additivity assumption adopted in Whitehead et al. (2006) by a combination of the revealed preference and stated preference data.

The combination of revealed preference and stated preference data for environmental valuation generally improves both types of willingness to pay estimates (Whitehead et al., 2005). Stated preference data can be used to estimate behavior and values beyond the range of revealed preference data, including nonuse values. Revealed preference data can be used to ground the stated preference data in reality and mitigate hypothetical bias. Also, additional observations may improve econometric efficiency of both types of estimates. McConnell (1990) provides the theory for data combination. Cameron (1992) empirically links a revealed preference model of continuous demand and a stated preference model of willingness to pay.

Whitehead (1995a) extends the McConnell (1990) results and identifies the price of recreation trips as an exogenous predictor of willingness to pay for quality change. One implication is that in an empirical model of willingness to pay the coefficient on recreation price provides an estimate of the change in demand (e.g., recreation trips) that would result from the quality change. Whitehead (1995b) argues that this result can be used to decompose willingness to pay into use and nonuse values. Willingness to pay and trip change models can be jointly estimated to more efficiently exploit the theoretical link (Huang, Haab and Whitehead 1997). In a more ad-hoc empirical specification Whitehead (2005) includes the predicted value of the

change in trips using stated preference data with a quality change as a determinant of willingness to pay. This model is most appropriately used when measurement of recreation price is problematic. In addition, this model can also be used to decompose willingness to pay into use and nonuse values.

Revealed preference research has examined the linkage between discrete choice models of recreational site selection and continuous choice models of recreational intensity with the inclusive value -- an index of the expected utility gained from recreation trips (Parsons, Jakus and Tomasi 1999). No study to date has examined the linkage between discrete choice models of recreation site selection and stated preference models of willingness to pay. In this paper we link discrete choice recreation demand, continuous choice demand and willingness to pay models with the inclusive value. We use the Saginaw Bay watershed hunting and fishing license holders subset of the data used by Whitehead et al. (2006). These data include information on the typical county of Saginaw Bay coastal marsh-based recreation, the number of annual Saginaw Bay coastal marsh-based recreation trips and willingness to pay for coastal marsh protection. In general the approach presented here has the potential to (a) test the convergent validity of revealed and stated preference data, (b) provide an indirect test for scope and (c) examine the proportion of use and nonuse values in willingness to pay. Our more limited goal is to further examine the willingness to pay decomposition for the Saginaw Bay study.

The Linked Site Selection – Willingness to Pay Model

The travel cost method (TCM) is a revealed preference approach to environmental valuation that is used to estimate the benefits of outdoor recreation activities (Parsons, 2003). A variation of the travel cost method is the site selection (i.e., random utility) model (Parsons,

2003). In the random utility model (RUM), it is assumed that individuals choose their recreation site based on differences in trip costs and site characteristics (e.g., wetland acreage) between the alternative sites. Analysis of data on recreation site choice enables estimation of the monetary benefits of any change in site characteristics.

Consider an individual who considers a set of $j = 1,...,m$ recreation sites. The individual utility from the trip is decreasing in trip cost and increasing in trip quality:

$$(1) \qquad u_{ij} = v_{ij}(y_i - c_{ij}, q_j) + \varepsilon_{ij}$$

where u is the individual utility function, v is the nonstochastic portion of the utility function, y is income, c is the trip cost, q is a vector of site qualities, ε is the error term, i indexes individuals, $i = 1, \ldots, n$ and j indexes recreation sites, $j = 1, \ldots, s, \ldots m$. The deterministic part of the utility function is linear

$$(2) \qquad v_{ij} = \alpha_c c_{ij} + \alpha_q q_j + \alpha_k^{/} z$$

where c_{ij} is the travel cost of individual i to site j, q_j is the quality of site j and α_k is a vector of $j - 1$ alternative specific constants interacted with income and perhaps other individual-specific variables, z. The random utility model assumes that the individual chooses the site that gives the highest utility:

$$(3) \qquad \pi_{ij} = \Pr(v_{ij} + \varepsilon_{ij} > v_{is} + \varepsilon_{is} \quad \forall\, s \neq j)$$

where π_{ij} is the probability that individual i chooses site j.

A site choice RUM is estimated using the multinomial logit model where the dependent variable is a choice among a set of alternatives and the independent variables are alternative specific (Haab and McConnell, 2002). For example, a recreationist choosing among a set of recreation sites might consider the travel costs to each site and the characteristics of each site. If the error terms are independent and identically distributed extreme value variates then the conditional logit site selection model results

$$(4) \qquad \pi_i = \frac{e^{v_i}}{\sum_{j=1}^{m} e^{v_s}}$$

The inclusive value is the expected maximum utility from the cost, quality characteristics of the sites and other aspects of the choice. The inclusive value, *I*, is measured as the natural log of the summation of the site choice utilities

$$(5) \qquad I(c,q,z;\alpha) = \ln\left(\sum_{j=1}^{m} e^{v_j}\right)$$

Hanemann (1999) shows that the compensating variation from a change in quality characteristics is:

$$(6) \qquad CV = \frac{I(c,q,z;\alpha) - I(c,q+\Delta q,z;\alpha)}{\alpha_c}$$

where *CV* is the compensating variation measure of welfare for each choice occasion and the marginal utility of income is α_c. Haab and McConnell (2002) show that the compensating variation for a quality change can be measured as

$$(7) \qquad CV(\Delta q_k) = \frac{\alpha_k \Delta q_k}{\alpha_c}$$

where q_k is one element of the q vector. The compensating variation of site access is

$$(8) \qquad CV(j) = \frac{-\ln(1-\pi_{ij})}{\alpha_c}$$

These welfare measures apply for each trip taken by the individuals in the sample. If the number of trips taken is unaffected by the changes in cost and/or quality, then the total willingness to pay is equal to the product of the per trip compensating variation and the average number of recreation trips, $\bar{x}$. If the number of trips taken is affected by the changes in quality then the appropriate measure of aggregate welfare must be adjusted by the change in trips. There are several methods of linking the trip frequency model with the site selection model (Herriges, Kling and Phaneuf, 1999; Parsons et al., 1999), we choose the original approach that includes the inclusive value parameter as a variable in the trip frequency model (Bockstael, Hanemann and Kling, 1987)[5]

$$(9) \qquad x = x\left[I(c, q, z; \alpha), z\right]$$

These models are typically estimated with count (i.e, integer) data models such as the Poisson or negative binomial models (Haab and McConnell 2002). Count data makes adjustments for the fact that trips are not continuous variables but integers (e.g., 0, 1, 2, etc). Recreation demand count data tends to be clustered at zero and low integer values. The Poisson estimates the probability of trips at each integer value

[5] This is also referred to as a participation model.

(10) $$\Pr(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}$$

(11) $$\ln(\lambda) = \beta_0 + \beta_1 I + \beta_2^{/} z$$

where x = 0, 1, 2, … is the number of trips, λ is the mean and variance of the trip distribution. The negative binomial model relaxes the equality restriction on the mean and variance of trips (Haab and McConnell, 2002).

Trips under various quality scenarios can be simulated by substitution of quality changes into the trip frequency model

(12) $$\hat{x}(\Delta q) = x\left[I\left(c, \Delta q, z; \alpha\right), z\right]$$

The total compensating variation of a quality change that might affect the number of trips is aggregated over the number of trips:

(13) $$CV(\Delta q_k) = \sum_{j=1}^{m}\left(\left[\hat{x}_j(\Delta q)\right]CV(\Delta q_k \mid j) + \left[\bar{x}_j - \hat{x}_j(\Delta q)\right]CV(j)\right)$$

The first component of the total value is the product of the average number of trips taken with the quality change and the value of the quality change. The second component of the willingness to pay is the product of the difference in trips and the willingness to pay for a trip to a particular site.

The contingent valuation method (CVM) can be used to estimate the willingness to pay for quality change (Mitchell and Carson, 1989; Boyle, 2003). The contingent valuation method is a stated preference approach that directly elicits willingness (and ability) to pay statements from

survey respondents. Respondents are directly asked about their willingness to pay (i.e., change in compensating variation) for environmental improvement. The CVM involves the development of a hypothetical market via household surveys. In the hypothetical situation respondents are informed about the current problem and the policy designed to mitigate the problem. Other contextual details about the policy are provided such as the policy implementation rule (e.g., provision point design) and the payment vehicle (e.g., a special fund). Finally, a hypothetical question presents respondents with a choice about the improvement and increased costs versus the status quo. Statistical analysis of these data leads to the development of willingness to pay estimates.

Willingness to pay (*WTP*) for a quality change is

$$v_i(c, y_i - WTP_i, q) = v_i(c, y_i, q - \Delta q) \tag{14}$$

where c is a vector of travel costs and Δq is the change in quality. The dual definition of willingness to pay is

$$\begin{aligned} WTP_i &= e(c, q - \Delta q, v_i) - y_i \\ &= s(c, q, \Delta q, y_i) \end{aligned} \tag{15}$$

where $y = e\big(c, q, v(c, q, y)\big)$ and $s(\cdot)$ is the variation function. Willingness to pay is decreasing in travel costs, increasing in quality and increasing in income (Whitehead, 1995a). The variation function can be specified with utility theoretic variables

$$WTP_i = \gamma_0 + \gamma_1^{/} c + \gamma_2 q^{/} + \gamma_3 y + \gamma_4 z \tag{16}$$

where $q^{/} = q - \Delta q$. The negative of the coefficient on the travel cost variable, with an adjustment for the marginal utility of income across quality states, provides an estimate of the additional trips that would be taken with the quality change. The marginal willingness to pay for quality change can be obtained from the coefficient on the quality variable.

The proposal of this paper is that, alternatively, the inclusive value can be included as an index of travel costs, quality and income

$$(17) \qquad WTP_i = \gamma_0 + \gamma_1 I(c, q, z; \alpha) + \gamma_2 z$$

Oftentimes, alternative contingent valuation scenarios are necessary to obtain variation on quality in order to estimate its marginal value. In this case, marginal willingness to pay for changes in quality can be obtained from the coefficient on the inclusive value and simulated changes in the inclusive value

$$(18) \qquad \frac{\partial WTP_i}{\partial q} = \gamma_1 \frac{\partial I(c, q, z; \alpha)}{\partial q}$$

Alternative contingent valuation scenarios are not needed in order to obtain estimates of marginal willingness to pay for quality with the inclusive value.

Considering the revealed preference and stated preference approaches, a test of the convergent validity of the revealed preference (*CV*) and stated preference (*WTP*) methods is

$$(19) \qquad \begin{array}{l} H0: CV(\Delta q) = WTP(\Delta q) \\ HA: CV(\Delta q) \neq WTP(\Delta q) \end{array}$$

Equality of value estimates would lend validity to both methods.

Survey and Data

The purpose of the "Saginaw Bay Coastal Marshes Survey" is to generate data for use in developing economic values for coastal marsh protection. The survey describes Saginaw Bay coastal marsh resource allocation issues, elicits information about coastal marsh-related recreation, inquires about attitudes regarding economic development, describes a coastal marsh protection program and elicits willingness to pay. It also obtains socio-economic information.

Names and addresses of all sportsmen living within the Saginaw Bay watershed were obtained under a special use agreement with the Michigan Department of Natural Resources (DNR). From this list, names were randomly selected. Three rounds of surveys were mailed between February and June of 2005. Ten days after each mailing, a reminder card was sent to all survey recipients. To help increase the response rate, the third round of surveys included an incentive. Survey recipients were notified that $1000 would be divided among five winners. Winners were randomly selected from the third round respondents and a check was sent to each.

For each of the 18 versions of surveys sent to sportsmen, 79 names were randomly selected from the DNR list, for a total of 1422 surveys. We obtained a response rate of 22% and, after deletion of cases with item nonresponse on important variables, we have a sample size of 251 (Table 1). The typical license holder household has 3 people with 0.82 children. The license holder sample is 79 percent male and 97 percent white. The average age is 48 years. Thirty-seven percent are members of conservation and/or environmental organizations and 8 percent owned

Saginaw Bay shoreline property. The average number of years in school is 14. Household income is $49 thousand.[6]

Respondents are asked about their Saginaw Bay coastal marsh-related recreation activities. These activities are defined as any trip where the respondent was on or near the water including the marshes where the typical plants are cattails, rushes, grasses, and shrubs. Fifty four percent of the sample had visited the Saginaw Bay or Saginaw Bay coastal marsh area for outdoor recreation or leisure. The license holders took an average of 6 coastal marsh recreation trips. Not all license holders took trips to Saginaw Bay. The recreation participants took an average of 11 trips. The primary recreation activity was fishing with 55 percent of the sample anglers. The most popular county for recreation trips was Bay County with almost 50 percent visiting there on a typical trip.

The survey elicited the willingness to pay for coastal marsh protection using the contingent valuation method. Respondents are told that 9000 of 18,000 acres of Saginaw Bay coastal marshes are currently protected and that the remaining privately owned marshes could be purchased and protected. A hypothetical "Saginaw Bay Coastal Marsh Protection Program" was introduced. Voluntary contributions would go into a "Saginaw Bay Coastal Marsh Trust Fund"

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[6] We also obtained a sample of the general population with a similar response rate and sample size but focus our analysis on the license holders sample in this paper. The results from the general population are generally consistent with those of the license holders except that the linkage between willingness to pay and the inclusive value is nonexistent.

to purchase *X* acres of coastal marsh. The acreage amount, *X*, was randomly assigned from three amounts 1125, 2500 and 4500.

Respondents are told that "Money would be refunded if the total amount is not enough to purchase and manage *X* acres. If the amount of donated money is greater than the amount required to purchase and manage *X* acres, the extra money would be used to provide public access and educational sites at Saginaw Bay coastal marshes." This is known as the provision point survey design (Poe, et al., 2002). The provision point design has been shown to minimize free riding bias in willingness to pay responses.

Then respondents are asked: "Would you be willing to make a one-time donation of money to the Saginaw Bay Coastal Marsh Trust Fund within the next 12 months?" For the license holder sample, 27 percent, 50 percent, and 23 percent would, would not, and did not know whether they would make a donation. Respondents who would be willing to make a donation are then told that "if about 1 percent (1 in 100) of all households in Michigan made a one-time donation of $*A*, the Trust Fund would have enough money to purchase and manage *X* acres of coastal marshes. Remember, if you made a one-time donation of $*A* into the Trust Fund, you would have $*A* less to spend on other things. Also remember that protected marsh would no longer be available for conversion to other uses." The dollar amount, $*A*, was randomly assigned from the following amounts: $25, $50, $75, $100, $150 and $200. The dollar amounts were chosen based on revenue streams required to purchase *X* acres of coastal marsh if 1 percent of all Michigan households made the donation.

Respondents are asked if they **"**would make a one-time donation of $*A* to the Saginaw Bay Coastal Marsh Trust Fund within the next 12 months?" Sixty-two percent, 42 percent, 36

percent, 42 percent, 26 percent, and 19 percent of the license holders were willing to pay $25, $50, $75, $100, $150 and $200.

One problem that arises with contingent valuation method surveys is hypothetical bias (Whitehead and Cherry, forthcoming). Hypothetical bias exists if respondents are more likely to say that they would pay a hypothetical sum of money than they would actually pay if placed in the real situation. Since economic values are based on actual behavior, hypothetical bias leads to upward biased estimates of economic value. One method that is used to mitigate hypothetical bias is the certainty rating (Champ and Bishop, 2001).

For those respondents who said that they were willing to pay we asked: "On a scale of 1 to 10 where 1 is "not sure at all" and 10 is "definitely sure", how sure are you that you would make the one-time donation of $*A*?" Thirty-four percent are definitely sure that they would pay and forty-percent are very sure that they would pay (i.e., their rating was 7, 8 or 9). To determine how likely respondents find the donation mechanism to work we ask "how likely do you think it is that 1 percent of all households in Michigan would make a one-time donation of $*A* to the Trust Fund within the next 12 months?" Forty-seven percent of the license holders thought that it would be somewhat likely or very likely.

Empirical Results

Revealed Preference

Recreation participants and non-participants are included in the analysis. Non-participants are those who took zero trips. The dependent variable for the site selection model is the typical county chosen for a coastal marsh-based recreation trip. We also include a

nonparticipation choice for those who do not take trips. The most popular county for recreation trips is Bay County with almost 50 percent visiting there on a typical trip. Twelve percent go to Iosco and Arenac Counties, 11 percent goes to Tuscola County and 24 percent go to Huron County on a typical trip. Forty-six percent do not choose any county.

Data on wetlands acreage and other measures of site quality for each Saginaw Bay county was provided by Ducks Unlimited (Table 2). Other variables used to explain recreation site selection are the travel costs to the county site, the number of water access points in the county site and National Forest acreage. We compute distance traveled from the home zip code of the respondent to the zip code of the most commonly visited city in the county of the typical recreation trip destination using ZIPFIP software, d_{ij} (Hellerstein, 2005). Travel cost per mile is set at $0.37, time costs are valued at one-third of the wage rate, and average miles per hour is 60: $c_{ij} = 0.37 \times 2 \times d_{ij} + [(0.33 \times y_i / 2000) \times (2 \times d_{ij})] / 60$. The average travel cost is $56, the average number of wetland acres in each county is 42,000, the average number of access points is 6 and the average number of National Forest acres in each county is 10 thousand.

In Model 1, we include travel costs, wetland acres, access points and acres of National Forest land as independent variables (Table 3). As expected, the probability of site choice decreases as the travel costs to the site increases. The probability of site choice is not affected by wetland acres or acres of National Forest land. The probability of site choice increases with access points.

In Model 2, we also include alternative specific constants interacted with income. In this model, the probability of site choice decreases as the travel costs to the site increases. Surprisingly, the probability of site choice decreases with wetland acres. This is likely due to the

inclusion of recreation nonparticipants in the model. In Whitehead et al. (2006), with nonparticipants excluded, the probability of site choice increases with wetland acreage. The probability of site choice increases with access points. The probability of site choice is not affected by National Forest land. The probability of site choice at each of the five counties, relative to nonparticipation, increases with income. This result indicates that coastal marsh recreation is a normal good.

We use the inclusive value computed from each of these models. We expect varying results depending on the inclusive value used and whether income is included in the linked models because the correlation coefficients between income and the inclusive values are significantly different. The correlation coefficient between the inclusive value from Model 1 and income is negative, $r = -0.33$. The correlation coefficient between the inclusive value from Model 2 and income is positive, $r = 0.52$. Nevertheless, the correlation coefficient between the inclusive values from Models 1 and 2 is positive, $r = 0.58$.

We estimate three negative binomial trip participation models. Model 1 includes the inclusive value estimated without income in the utility function (from Model 1 of Table 2) and a separate income variable. Trips increase with the inclusive value and income. The inclusive value coefficient primarily reflects the price effect. As travel costs fall (the individuals live closer to the recreation destination) the inclusive value increases.

Model 2 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) without a separate income variable. Trips increase with the inclusive value. In this model, the inclusive value coefficient reflects the price effect and the income effect. As income increases, the individual is more likely to participate in recreation and, therefore, take

more trips.

Model 3 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) with a separate income variable. Trips increase with the inclusive value and decrease with income. Holding the effect of income on recreation participation constant, as income increases the individual takes fewer trips. From a statistical standpoint, Model 1 is preferred with a higher log-likelihood function value.

Stated Preference

The dependent variables in the willingness to pay analysis are whether the respondent is willing to pay something above zero ("donate") and, if so (n = 129), willing to pay more than the requested donation ("give"). Following Groothuis and Whitehead (2002) the "don't know" responses are recoded to "no" responses for a conservative estimate of willingness to pay. Since economic values are revealed by behavior, correction of hypothetical bias is necessary to develop more accurate willingness to pay estimates. We recode "give" responses where the respondent is not sure that they would be willing to pay, these respondents answered less than 7 on the follow-up certainty scale, to "no" responses. The natural log of the bid ($\$A$) amount is used to improve statistical fit.

The two willingness to pay decisions (e.g., donate and give) are analyzed separately with the logit model. The probability of a "yes" response is the probability that willingness to pay, WTP, is greater than the bid amount, A (Cameron, 1988)

$$\begin{aligned} \Pr(donate) &= \Pr(WTP > 0) \\ &= \Pr\left(\frac{\lambda' z}{\kappa}\right) \end{aligned} \tag{20}$$

$$\text{(21)} \quad \begin{aligned} \Pr(give) &= \Pr(WTP > A) \\ &= \Pr\left(\frac{\theta' z - \ln A}{\kappa}\right) \end{aligned}$$

where λ and θ are vectors of coeffcients, z is a vector of independent variables and $\frac{-1}{\kappa}$ is the coefficient on the log of the bid amount. Median willingness to pay is (Haab and McConnell, 2002)

$$\text{(22)} \quad \begin{aligned} WTP &= \exp\left(\kappa\left[\theta' z\right]\right) \\ &= \exp(\gamma' z) \end{aligned}$$

The t-statistics are developed using standard errors approximated by the Delta Method (Cameron, 1991).

The willingness to pay results are presented in Table 4. In addition to the inclusive value we include the log of the bid amount and the wetland acreage in both "donate" and "give" models. Since the data was collected with a mail survey respondents could read the entire survey before answering any question. It is therefore possible that price and scope effects may be found in the donate model, although theory would not guide the inclusion of these variables. Conservation and/or environmental organization membership and income are the only socioeconomic variables included. We also include a dummy variable equal to one if the respondent thinks it is likely that enough Michigan residents would make the required donation for the program to be a success. The variable is equal to zero otherwise.

We present four models. Model 1 includes the inclusive value estimated without income in the utility function (from Model 1 of Table 2) and a separate income variable. Model 2

includes the inclusive value estimated without income in the utility function and without income as a separate variable (from Model 1 of Table 2) without a separate income variable. Model 3 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) with a separate income variable. Model 4 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) without a separate income variable.

We first describe some general results and then turn our attention to the inclusive value. In each model, as the bid amount increases the probability of "donate" and "give" responses decreases. The bid variable influences the decision of whether to donate any amount of money and whether to donate the bid amount. In each model respondents who are organization members are more likely to be willing to donate some positive amount of money for coastal marsh protection and more likely to give more than the bid amount.

An important test of the validity of willingness to pay responses is whether willingness to pay increases with the quantity of the good being purchased. This is known as the scope test (Whitehead, Haab, and Huang, 1998). The scope test results are mixed. In models 1 and 3, with income included as a separate variable, increases in scope makes it more likely that the respondents will donate some amount of money. However, in none of the models is marsh acreage a significant determinant of whether the respondent would give more than the bid amount. Note that failure to pass the scope test does not necessarily invalidate the willingness to pay values. Economic theory only requires that willingness to pay be non-decreasing with quantity.[7]

[7] Recent research in behavioral economics indicates that individuals do not always follow the

The provision point design is intended to provide respondents with incentives to reveal their true willingness to pay. One reason why respondents might state that they would not donate even if their willingness to pay is above the requested donation is that they believe the money would be wasted if total donations are not sufficient to fund the program. With the provision point design respondents are told that if that occurs, their money would be refunded. Survey respondents who did not believe that the donations would be sufficient were less likely to be willing to pay the bid amount. This result is further explored by Groothuis and Whitehead (2006).

Whitehead et al. (2006) adopt the theoretically preferred empirical specification by including the typical trip travel cost for users and the minimum travel cost for nonusers. The coefficient on this variable is not statistically significant which suggests that the willingness to pay estimates are nonuse values. The results with the inclusive value included in the willingness to pay model are mixed but generally support the results in Whitehead et al. (2006). In Model 1, with income excluded from the inclusive value but included separately in the model, the coefficient on the inclusive value is negative in the "donate" model and statistically insignificant in the "give" model. The same result is found in Models 2 and 3 without income in the inclusive value or as a separate variable and with income included in the inclusive value and included as a

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dictates of neoclassical consumer theory. Heberlein, et al. (2005) found that individual respondents do not pass the scope test internally for a variety of reasons. Market forces act to discipline irrational behavior for market goods. In valuation surveys this behavior is allowed to flourish. They conclude that behavior that flows from complex individual preferences and does not strictly follow neoclassical economic theory should not be considered invalid.

separate variable, respectively. The coefficient on income is positive and statistically significant in Models 1 and 3 in both willingness to pay decisions.

Models 1, 2 and 3 support an interpretation of willingness to pay as nonuse value since it does not vary in the expected direction with the inclusive. These results indicate that those with higher levels of expected maximum utility from coastal marsh recreation are less likely to be willing to donate anything for marsh protection. A naïve interpretation of this result is that it is consistent with the negative values for marsh protection found in the recreation demand model. However, the negative value result from the recreation demand model is likely due to the predominant choice of nonparticipation and the zero value of wetlands associated with that choice. Another interpretation of the willingness to pay result is that recreation nonusers hold nonuse values while recreation users do not hold nonuse values.

In contrast to Models 1-3, Model 4, with income included in the inclusive value and excluded as a separate variable, provides a different interpretation. The inclusive value is not a determinant of the decision to donate money to marsh protection but the probability of giving more than the bid amount is positively affected. This result suggests that willingness to pay is decreasing in travel cost and increasing in income and that willingness to pay contains a large component of use values. It is likely, however, that the inclusive value is picking up the income effect. It is most likely that the inclusive value is capturing ability to pay rather than the utility of recreational use of the coastal marsh.

Conclusions

We have explored the linkage between recreation demand and willingness to pay models. We have two goals. First, we further consider the decomposition of willingness to pay into use and nonuse values. If contingent valuation estimates of willingness to pay are comprised mostly of nonuse values then value estimates from revealed preference and stated preference models are additive. Second, we propose an alternative model for linking revealed preference and stated preference models of recreation when a single travel cost measure is difficult to obtain. We show that this model can be used to test convergent validity and offers an alternative scope test that does not rely on split-sample contingent valuation scenarios.

Our results with the Saginaw Bay coastal marsh data are mixed. In three of the four models estimated the inclusive value is negatively related to the willingness to donate but unrelated to the willingness to give more than the suggested bid amount. This result suggests that recreation nonusers hold nonuse values while recreation users do not hold nonuse values. As such, we believe that much of the willingness to pay estimate is comprised of nonuse values and the additivity assumption adopted by Whitehead et al. (2006) is appropriate.

The lack of an expected result may also arise from an incompatibility between the revealed preference and stated preference data. The stated preference data results from a scenario where respondents are asked to help protect an existing resource. Without this protection, the quality of future recreation resources might diminish. The revealed preference data results from existing opportunities. Future research should explore recreation demand and willingness to pay scenarios that are more tightly linked.

References

Boyle, Kevin J., “Contingent Valuation in Practice,” chapter 5 in A Primer on Nonmarket Valuation, edited by Patricia A. Champ, Kevin J. Boyle and Thomas C. Brown, Kluwer, 2003.

Cameron, Trudy Ann, “A new paradigm for valuing non-market goods using referendum data: Maximum likelihood estimation by censored logistic regression,” Journal of Environmental Economics and Management, 15(3): 355-379, 1988.

Cameron, Trudy Ann, “Interval Estimates of Non-market Resource Values from Referendum Contingent Valuation Surveys,” Land Economics, 67, 413-421, 1991.

Cameron, Trudy Ann, “Combining Contingent Valuation and Travel Cost Data for the Valuation of Nonmarket Goods,” Land Economics 68(3):302-317, 1992.

Champ, Patricia A., and Richard C. Bishop, “Donation Payment Mechanisms and Contingent Valuation: An Empirical Study of Hypothetical Bias,” Environmental and Resource Economics, 19:383-402, 2001.

Groothuis, Peter A., and John C. Whitehead, “Does Don't Know Mean No? Analysis of 'Don't Know Responses in Dichotomous Choice Contingent Valuation Questions,” Applied Economics, 34, 1935-1940, 2002.

Groothuis, Peter A., and John C. Whitehead, “Scenario Rejection and the Provision Point Mechanism: Their Influence on the Willingness to Pay in Contingent Valuation,” Paper Presented at the Southern Economic Association Meetings, Charleston, South Carolina,

2006

Haab, Timothy C., and Kenneth E. McConnell, Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation, Northampton, MA: Edward Elgar, 2002.

Heberlein, Thomas A., Matthew A. Wilson, Richard C. Bishop and Nora Cate Schaeffer, "Rethinking the Scope Test as a Criterion for Validity in Contingent Valuation," Journal of Environmental Economics and Management, 50, 1-22, 2005.

Hellerstein, Daniel, ZIPFIP Databases and Software, Washington, DC: US Department of Agriculture, Economic Research Service, 2005.

Hoehn, J.P., F. Lupi, M. D. Kaplowitz, "Untying a Lancastrian bundle: valuing ecosystems and ecosystem services for wetland mitigation," Journal of Environmental Management 68: 263-272, 2003.

Huang, Ju-Chin, Timothy C. Haab and John C. Whitehead, "Willingness to Pay for Quality Improvements: Should Revealed and Stated Preference Data Be Combined?" Journal of Environmental Economics and Management, 34(3): 240-255, 1997.

Jaworski, E., and C. N. Raphael, "Fish, Wildlife and Recreational Values of Michigan's Coastal Wetlands," Great Lakes Shorelands Section, Division of Land Resource Programs, Michigan Department of Natural Resources, 1978.

Lupi, R, M. D. Kaplowitz, and J.P. Hoehn, "The economic equivalency of drained and restored wetlands in Michigan," American Journal of Agricultural Economics, 5: 1355-1361, 2002.

McConnell, K.E., “Models for Referendum Data: The Structure of Discrete Choice Models for Contingent Valuation,” Journal of Environmental Economics and Management, 18(1):19-34, 1990.

Mitchell, Robert Cameron and Richard T. Carson, Using Surveys to Value Public Goods: The Contingent Valuation Method, Resources for the Future: Washington, DC, 1989.

Mullarkey, D., “Contingent Valuation of Wetlands: Testing Sensitivity to Scope,” PhD Dissertation, University of Wisconsin, 1997.

Parsons, George R., “The Travel Cost Model,” chapter 9 in A Primer on Nonmarket Valuation, edited by Patricia A. Champ, Kevin J. Boyle and Thomas C. Brown, Kluwer, 2003.

Parsons, George R., Paul M. Jakus and Ted Tomasi, “A Comparison of Welfare Estimates from Four Models for Linking Seasonal Recreational Trips to Multinomial Logit Models of Site Choice,” Journal of Environmental Economics and Management, 38(2): 143-157, 1999.

Poe, Gregory L., Jeremy E. Clark, Daniel Rondeau, and William D. Schulze, “Provision Point Mechanisms and Field Validity Tests of Contingent Valuation,” Environmental and Resource Economics, 23, 105-131, 2002.

van Vuuren, W. and P. Roy, “Private and social returns from wetland preservation versus those from wetland conversion to agriculture,” Ecological Economics, 8: 289-305, 1993.

Whitehead, John C., “Willingness to Pay for Quality Improvements: Comparative Statics and Theoretical Interpretations of Contingent Valuation Results,” Land Economics, 71, 207-215, 1995a.

Whitehead, John C., “Differentiating Use and Non-use Values with the Properties of the Variation Function,” Applied Economics Letters, 2, 388-390, 1995b.

Whitehead, John C., “Combining Contingent Valuation and Behavior Data with Limited Information,” Resource and Energy Economics, 27, 143-155, 2005.

Whitehead, John C., and Todd L. Cherry, “Mitigating the Hypothetical Bias of Willingness to Pay: A Comparison of Ex-Ante and Ex-Post Approaches,” Resource and Energy Economics, forthcoming.

Whitehead, John C., Peter A. Groothuis, Thomas J. Hoban and William B. Clifford, "Sample Bias in Contingent Valuation: A Comparison of the Correction Methods," Leisure Sciences, 16, 249-258, 1994.

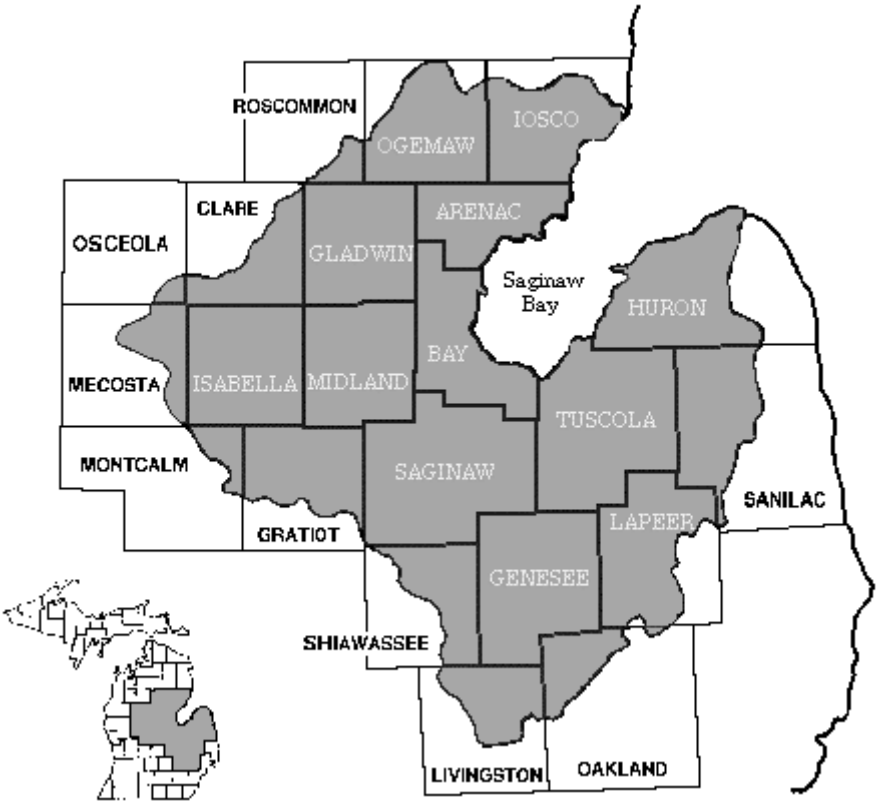
Whitehead, John C., Peter A. Groothuis, Rob Southwick and Pat Foster-Turley, “Economic Values of Saginaw Bay Coastal Marshes,” No. 06-10, Working Papers from Department of Economics, Appalachian State University, 2006.

Whitehead, John C., Timothy C. Haab, and Ju-Chin Huang, "Part-Whole Bias in Contingent Valuation: Will Scope Effects Be Detected with Inexpensive Survey Methods?" Southern Economic Journal, 65, 160-168, 1998.

Whitehead, John C., Subhrendu K. Pattanayak, George L. Van Houtven and Brett R. Gelso, "Combining Revealed and Stated Preference Data to Estimate the Nonmarket Value of Ecological Services: An Assessment of the State of the Science," No. 05-19, Working Papers from Department of Economics, Appalachian State University, 2005.

Woodward, R.T. and Y.S. Wui, 2001, "The economic value of wetland services: a meta-analysis, Ecological Economics, 37: 257-270.

Figure 1. Saginaw Bay Watershed



Combining Stated and Revealed Preference: Comments on Huang-Parsons-Zhao-Poor, Milon-Scrogin, and Whitehead-Groothuis-Southwick

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Each of these papers combines a revealed preference analysis, either travel cost or hedonics, with a stated preference survey. Revealed preference on its own is informative but difficult: the data collection and model construction (making the imperfect data yield at least some welfare-relevant results) are always a steep challenge. Stated preference too is informative but difficult; model construction is easier, a bit, but data collection is harder. Revealed preference plus stated preference, as these authors have embarked on, is doubly ambitious. But is it informative? Is the whole greater than the sum of the parts?

1. Advantages and Disadvantages of Combining RP and SP

There are several ways in which the whole might be greater than the sum of the parts. Per-survey costs may be cheaper. A related advantage is that the stated-preference question can be targeted toward users, as both HPZP and WGS do. This may or may not be desirable, of course.

Perhaps the most important conceptual advantage is that the combination of stated and revealed preference data can provide a test of convergent validity. In the context of travel cost analysis, revealed preference reigns supreme: Actual visits to a recreation area tell us something about individual tastes towards the recreational experience. If stated-preference results do not reveal the same qualitative tastes then the particular stated-preference survey was probably poorly designed.

The potential disadvantage from combining RP and SP is that the stated preference survey gets insufficient attention. It gets insufficient attention both from the survey designer and the respondent. On-site valuation surveys, such as HPZP, are hectic affairs since respondents are almost always eager to get one with their recreation. There is not enough time for the subject to respond thoughtfully.

Mail surveys suffer because it is very difficult – impossible, really – because of the non-response problem. Mail surveys have low response rates (there are lots of unreturned surveys) and these non-respondents are not a random sample of values. I would like to urge the profession to drop mail surveys or, failing that, to explore the contexts in which mail surveys yield the same results as in-person (not telephone) surveys. Non-respondents likely do not represent a random sample of values even when demographic characteristics are the same for respondents and non-respondents. The unobserved component of tastes – that is, the component not related to income, education, location, or other variables – is important. But it is almost surely lost in a mail-survey unless there is a very high response rate.

2. Statistics

Economists rely too heavily on statistical significance. Many articles report significance without even mentioning the magnitude of the estimated coefficient and its implications. See McCloskey for a discussion of the prevalence of this feature in economic writing and a criticism. These research articles fall in with this pattern. WGS mention the statistical significance of their coefficient on Acres in their scope test but do not help the reader understand the actual coefficient. HGPZ do the same on their erosion measure. I urge the authors to focus on the estimated coefficients and what we can learn from them, leaving little more than a nod toward statistical significance.

The problem is that *0 is not a relevant null hypothesis for most valuation studies*. This problem is sufficiently widespread and sufficiently misunderstood (as was apparent at this EPA conference) that it is worth giving an example.

Suppose we wanted to know whether older individuals placed a higher value on a statistical life (VSL) than did lower individuals. An empirical investigation yields a coefficient of -0.2 on age (say, a dummy variable indicating whether the respondent is older than the author) with a standard error of 0.16. The absolute value of the t-statistic is 1.25, which indicates that the estimated coefficient is not significantly different from zero.

Does this result mean that older individuals have the same VSL as younger ones? Of course not; the researchers' *best guess* is that older individuals have a VSL that is 20 percent lower. Indeed, the whole point of estimation is that -0.2 is the researcher's considered assessment of this relationship. To argue that the VSL is the same for both groups is silly or, to be more accurate, is no more informative than arguing that the VSL for older individuals is *40 percent* lower. If a coefficient β is insignificantly different from 0, it is insignificantly different from 2β. If this latter conclusion seems fatuous, the reader should recognize that it is statistically analogous to the claim that the VSL is the same for the two groups.

Readers might wonder then whether t-statistics or standard errors have any role at all to play. For valuation, at least, the answer is "not much." Standard errors tell us how confident we can be about a coefficient. The policy context has to tell us the implication of this imprecision. To put this another way, the estimated magnitude of a relationship and the precision of our estimate are two separate findings. Statistical significance conflates these.

I refer readers to the insightful and voluminous work by McCloskey on this issue, including many concrete examples.

3. Relationship between WTP and Inclusive Value

WGZ look at the relationship between WTP and Inclusive Value, the latter a statistical construct from a nested logit. Their goal is admirable but the paper (as presented at the conference) did not characterize this relationship quite right. The correct relationship is:

WTP (for a change in acres) = *derivative* of Inclusive Value with respect to. Acres

Note that this relationship is definitional, not "explanatory." Therefore, it does not yield an obvious role for any other explanatory variables. It is not clear how to "test" this relationship.

4. Willingness to Pay and the Voluntary Contribution Problem

WGS elicit willingness-to-pay by asking individuals for a potential contribution to a land conservancy. This set-up is fraught with peril. Individuals can contribute to a land conservancy independently from the survey. This opportunity makes it difficult to interpret the survey responses. If an individual says she is willing to donate $25 but has is not currently a donor and, perhaps, has never previously donated, then the researcher should be suspicious of the response.

This is not only a problem of survey design; it is a problem of free-riding, a problem that is notoriously difficult to overcome.

Note that most WTP models assume that the public good is available only through the proffered mechanism. This assumption is not valid for the land conservancy situation. It may be violated more widely, for lots of valuation circumstances, an issue that is worth investigating further. When the assumption is violated, WTP reflects a combination of utility parameters (individual taste) and market prices or opportunities. We are interested in a pure inference of the former. Separating these two is difficult.

5. Amenity Values and Ecological Values

I started my comments with the recognition that revealed preference analysis was difficult because of both data collection and model building. The MS research illustrates both of these points. The data collection and analysis are an astounding feat. This is a rich data set.

The model raises many difficult questions. Wetlands affect the location and quantity of land available for building; in other words, wetlands affect both demand and supply. In some instances, wetland preservation is endogenous (to the local community), so it is not always straightforward to examine the effects of preserved vs. non-preserved wetlands. Finally, even when these concerns can be dealt with, the remaining estimates tell us about the amenity value of a wetland (whether it is scenic; whether it smells) but not about its ecological value – namely, the services is provides to the general ecology. The ecological services are hard to define and measure but most of those services do not accrue specially to people who live close to the wetland versus 1, 5, or 10 miles away. Note that a painstaking exegesis of the ecological services is necessary in order to know how these services are used and how valuable or necessary proximity is to take advantage of these ecological services.

It is not hard to image a situation in which individuals prefer to live close to a sweet-smelling wetland when in fact a foul-smelling one provides a much higher volume of ecological services. The resulting housing-price gradient would reflect the amenity value (in this case negative), but the ecological value is missing.