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Valuing a Spatially Variable Environmental Resource: Reducing Non-Point Source Pollution in Green Bay, WI

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Abstract.
This article investigates the value of reducing non-point source pollution in Green Bay, WI. Using stated preference methods, we find the lower bound on the benefits of reducing runoff enough to universally increase water clarity by four feet is greater than $9 million annually. Using a unique survey design, we show that because current water clarity in Green Bay is spatially variable, the value that a household places on this universal improvement depends on the distance of the household's residence from the Bay *and* on the particular geospatial location of the residence. This has important implications for estimating aggregate benefits.

KEYWORDS: water quality; non-point source pollution; nonmarket valuation; contingent valuation; spatial correlation

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I. Introduction

Nutrient runoff reduction has been an environmental priority in many watersheds, including those that feed Green Bay, Lake Michigan, but it is often politically difficult to undertake because it is costly, costs are often inequitably distributed, and the benefit is often highly uncertain. Good policy effectively articulated should address these concerns. In this article we focus on the last question: What are the benefits of runoff reduction in Green Bay, Lake Michigan?

Runoff from many sources carries nutrients and sediments into Green Bay and its tributaries. In an attempt to improve water clarity and reduce algae blooms in lower Green Bay, efforts are being made to reduce runoff from all sources (WI DNR 2006). Valuing improvements in water quality has long been a staple in the environmental economist's toolbox. (see, for instance, Smith and Desvouges 1986). Despite this long history, there is little guidance in how to conduct a valuation study for a large body of water with significant spatial variability of water quality, as exists in Green Bay. The issue can be summarized with a simple example. If two identical households live at different ends of a large water body, with the water quality relatively poor at one end and relatively good at the other, would the households differ in the value they place on a uniform improvement in water quality? If so, how does the analyst capture the differential value the households place on the improvement? The maps in Figure 1 illustrate the significance of this issue for water clarity improvements in Green Bay. The upper map shows current water clarity in the Bay. The red at the south end of the Bay denotes water clarity of less than 1 foot; the blue at the north end denotes water clarity greater than 11 feet. A uniform 4-foot improvement in water clarity in the Bay increases water clarity in the south end of the Bay to 4-5 feet, and increases water clarity in the north end to over 15 feet. If the Bay is considered by households to be a single entity defined only by its *average* water quality –the usual assumption in the literature—then the benefit of this 4-foot improvement in water clarity might depend on the *distances* of households to the Bay, but *not* otherwise on their geospatial location with respect to the Bay. If, on the other hand, households view the Bay as a quilt of water clarity patches, then the value they place on the 4-foot improvement depends on their geospatial location; the value a household places on the improvement depends not only on the distance to the Bay, but on whether the household is closer to the south end or the north end.

The current literature contains a rich variety of approaches to estimating the value of water quality improvements. Quantitative measures of water quality have included water level (Lansford and Jones 1995; Eisworth et al 2000), abundance of fecal coliform (Leggett and Bockstael 2000), and water clarity (Poor et al 2001; Gibbs et al 2002; Boyle, Poor, and Taylor 1999). Other studies focus on qualitative measures of improving the *functionality* of the water body, with the most common such measure being the water quality ladder developed by Resources for the Future. First developed by Vaughan (1986), and made more familiar through Mitchell and Carson's work (Mitchell and Carson 1989; Carson and Mitchell 1993). The water quality ladder presents water quality on a scale from 0 (worst) to 10 (best), with each level represented as the rungs of a ladder. Various rungs are associated with certain recreational uses. For example, fishable water quality is rung 5, but swimmable water quality is rung 7. While some researchers have expressed concern about the use of the water quality ladder (Magat et al 2000), it remains the dominant method for describing water quality improvements in stated preference studies (Johnston et al 2005). Even when the "ladder" is not explicitly referred to, qualitative measures (eg., "boatable", "fishable", "high wildlife abundance", "low fishing quality") are very common in stated preference studies.

The spatial variability of water quality on a water body makes implementation of a water quality ladder impractical, and raises two questions for using survey data to estimate the welfare effect of a change in a quantitative measure of water quality. The first is how to communicate this spatial variability to survey respondents, and the second is how to account for this spatial variability in the econometric model from which welfare estimates are derived. Using GIS data on water clarity in Green Bay, we designed a unique survey instrument to estimate household willingness to pay (WTP) for a runoff reduction program that would uniformly increase water clarity throughout the Bay. The survey included color-coded water clarity maps of the Bay (as exemplified by the aforementioned maps of Figure 1) indicating the effect of the nutrient reduction program on the Bay's water clarity at a spatial resolution of 30-by-30 meters. The econometric model allows us to identify the extent to which household WTP for water clarity improvements is driven by improvements in the clarity of water closest to the household, as opposed to the overall improvement in the Bay. Results indicate that accounting for the uneven spatial distributions of both households and water quality has a significant impact on the estimated aggregate WTP for the region. This is the case because a) the value that households place on the reduction program depends in part the initial water clarity closest to their residence, and b) the dirtiest water in the Bay –the water that improves in greatest proportion from a uniform improvement in water clarity—is relatively close to population centers.

The study area and GIS data are described in section 2. Section 3 describes the stated preference survey, focusing on our use of GIS-based water clarity maps to personalize the water clarity improvement scenario presented to respondents. Section 4 presents the econometric model. Section 5 presents the results, including the aggregate WTP for the water quality improvement, and section 6 concludes.

II. Study Area and GIS Data Description

Green Bay is a large Bay of Lake Michigan (118 miles long, 23 miles at its widest point) separating Wisconsin's Door Peninsula from the rest of Wisconsin and the upper Peninsula of Michigan. Several rivers drain into the bay. The largest is the Fox River. Along the banks of the Fox are many urban areas and the largest concentration of paper mills in the world. A great deal has been done over the years to control pollution from these and other point sources. The watershed also includes a significant amount of agricultural land. Runoff from farms, highways, construction sites, and residential and urban neighborhoods carries nutrients and sediments into Green Bay and its tributaries (WI DNR 2006). In an effort to improve water clarity and reduce algae blooms in lower Green Bay, efforts are being made to reduce runoff from all sources.

The study area of this application includes only those 14 townships that form the shoreline of the southern portion of Green Bay. This area includes portions of four counties (Brown, Door, Kewaunee, and Oconto). We limited the study area to these townships for two practical reasons. First, limiting the study population to those households closest to the Bay increases the likelihood that respondents will have a basic familiarity with the Bay and understand the water quality issues. Second, the cost of environmental cleanup is increasingly falling on local governments that generally consider the costs and benefits to the local population only. This is particularly evident in the grant programs administered by the Wisconsin Department of Natural Resources to aid local governments in their runoff reduction efforts (Heaton-Amrhein and Holden 2005). Focusing the analysis on the local population makes the analysis more relevant to this political reality. It follows, though, that the aggregate welfare estimates reported in this study represent a lower bound on total social welfare, since undoubtedly many people outside the 14 townships of the study area value improved water clarity in Green Bay.

Water clarity data

Water clarity is traditionally measured with a Secchi disc, an 8-inch metal disc painted black and white. The disc is lowered into the lake until it cannot be seen and then raised until visible. The average of these two depths is the Secchi depth (Dobson 2004). Secchi depth can vary greatly with both time and space, and while the temporal variability is easily addressed by averaging Secchi measurements taken at the same place at different times, accounting for spatial variability via Secchi measurements in a large water body like Green Bay is either too crude (interpolation among a small number of measurement locations), or too expensive (interpolation among a large number of measurement locations).

To address this issue, we used data available from the Environmental Remote Sensing Center at the University of Wisconsin-Madison. Chipman et al (2005) developed a procedure that uses water clarity maps from the MODIS satellite to calibrate high resolution Landsat images to produce high resolution satellite-derived lake water clarity maps. The MODIS based maps have good seasonal averages of mean water clarity, measured in Secchi disk transparency and calibrated with actual field measurements, but have a low spatial resolution of only 250 to 500 meter pixels. The Landsat images have a much higher resolution, and comparing the reflectance measures from these images to the MODIS-derived water clarity data results in a water clarity map with a 30 meter pixel resolution. In shallow areas, a portion of the observed radiance measured in the Landsat images comes from the bottom of the Bay, and so is not directly related to water clarity. To correct for this, areas believed to be “optically shallow” were assigned a Secchi depth equal to the average Secchi estimate from adjacent non-shallow areas (Chipman et al 2005). These data were provided as a raster data file and viewed using ArcGIS. The raster data layer divides the southern portion of Green Bay into 1,325,028 pixels measuring 30 m by 30 m each, with Secchi depth reported for each pixel, measured in $1/16^{th}$ of a meter.

Parcel data

Parcel data for towns in the study area were necessary for two reasons: to draw the survey sample, and to calculate the aggregate social benefit of water clarity improvements in the Bay. Digitized parcel maps were obtained from county land records offices. Based on the parcel attributes available with these data, single family residential parcels less than 35 acres were identified. We included only these non-farm parcels for reasons we explain later in this section. Parcels were separated into two groups, bayfront and inland properties, the owners of which composed the eligible population for the stated preference survey. Table 1 shows the population, total number of parcels, and number of parcels considered relevant to this study for each of the four counties of the study area.

III. The Stated Preference Survey

A mail survey of property owners in the study area was conducted to elicit willingness to pay (WTP) for reduced non-point source runoff. Each property owner in the sample was mailed a survey booklet and two water clarity maps. The booklet included a description of the runoff reduction program, a written description of the two maps, a series of attitudinal and demographic questions, and a referendum-based CV question. The description of the runoff reduction program explained the link between runoff and water clarity and the possible negative impacts of poor water clarity can have on wildlife and recreation. It stated the runoff reduction program would likely improve water clarity by four feet throughout Green Bay. It also explained that runoff does not affect the quality of drinking water and is not a significant source of PCBs, a toxic chemical found in Green Bay and its tributaries that has received a great deal of attention in the area.

The maps included in the survey were intended to communicate the current spatial variability in water clarity in the Bay, as well as the spatial variability expected after the runoff reduction program. Examples are in Figure 1. The maps are color-coded, with a legend indexing the color scale to Secchi depth. The maps were generated with ArcGIS by overlaying the water clarity data described above onto Landsat images of the surrounding counties. The first map depicts the current summer average water clarity in Green Bay. The second map depicts a 4-foot improvement in water clarity throughout the Bay, the likely result of a proposed runoff control program. Each map includes an inset showing a close-up of water clarity closest to the respondent's property.

Following the scenario description, respondents were asked the following dichotomous choice CV question,

> "If you were voting in a referendum on steps to reduce nutrients and runoff into Green Bay and the cost to your household in increased state and local taxes would be $____ per year for the foreseeable future, how would you vote?"

The survey booklet and maps were initially mailed to a pretest sample of 30 property owners. Based on these responses and follow-up phone interviews, a final version of the survey was administered during the summer and fall of 2005. Six bid amounts of $50, $100, $300, $500, $700, and $1000 were used. To ensure adequate coverage of bayfront properties, the sample was stratified so 500 bayfront and 500 inland residential properties were included. In addition, the inland properties were stratified by county to match the county distribution of bayfront properties. The final sample included 206 bayfront and

204 inland properties in Door County, 30 of each type in Kewaunee County, 158 of each in Brown County, and 107 of each in Oconto County. Figure 2 depicts the location of the sampled properties within the study area. Further details of the sampling and administration of the survey can be found in Moore (2006). Table 2 shows the responses rate by offer amount. Overall, the response rate was high and similar across most offer amounts. Bayfront property owners responded at a higher rate than inland property owners (66% versus 56%, respectively) and the two counties in the northern part of the study area, Door and Oconto, had higher response rates than the two counties in the south (65% versus 55%, respectively).

Given the novelty of the maps as a means to communicate spatial variability in a stated preference study, we asked respondents to compare the water clarity information depicted in the map to their own observations of water clarity near their property and in the Bay as a whole. Responses to these questions suggest that respondents found the maps easy to understand and helpful for informing their decision regarding the CV question. Only 13% of the respondents answered “I don’t know” when asked whether the map was consistent with their own observations of water clarity near their property. Of the remaining responses, 14% thought water clarity is actually better than the map depicts, 68% thought the map was accurate, and 18% felt water clarity is worse than the map depicts. Based on these results, we conclude that not only did respondents understand the general information provided by the maps, but also that they are willing and able to process this information and relate it to prior knowledge. We do not believe that the added “cognitive burden” engendered by the maps reduced our overall response rate or negatively impacted the quality of the responses received. That said, without a control group it is not possible to test hypotheses related to how the inclusion of the maps impacted responses to the valuation question, and further exploration of this issue is needed.

IV. Econometric model

The standard approach to estimating willingness to pay (WTP) for a change in environmental quality is to model WTP as a function of a vector of individual characteristics, *Z*, and a random component, *ε*,

$$WTP = \alpha Z + \varepsilon \,, \tag{1}$$

in which case the respondent answers "Yes" to the referendum question if her WTP exceeds the offer amount *b*, and "No" otherwise. Assuming the error component of equation (1) has an iid Gumble distribution across the population, the probability of a "Yes" response takes the familiar logit form,

$$\Pr("Yes") = \frac{e^{\tilde{\alpha}Z - \beta b}}{1 + e^{\tilde{\alpha}Z - \beta b}} \,, \tag{2}$$

Where *b* is the offer amount and the money-metric coefficients α in (1) are found by re-scaling, $\alpha = \tilde{\alpha}/\beta$. The log likelihood function maximized to obtain estimates of parameters $\{\tilde{\alpha}, \beta\}$ is simply the sum of (2) over all respondents. In the discussion below, we refer to this basic specification as the "Base Model".

In the case at hand, we include three variables in *Z.* The first measures the frequency with which the respondent sails on Green Bay, and the second measures the frequency with which the respondent hikes along the Bay's shoreline. Both of these variables were measured on a five point scale, with "1" indicating "never" and "5" indicating "very often". The third variable is household income, recorded as one of three income groups[i].

In discrete choice models such as required to model responses to the survey referendum question, correlation of the random component ε across observations generates biased parameter estimates. In this study, the primary concern with respect to correlation across responses in the Base Model is spatial correlation; we would expect respondents who live far from Green Bay to have a different willingness to pay for runoff reduction than respondents who live close to the Bay. The remainder of this section describes two models of increasing complexity that expand upon the Base Model to eliminate spatial correlation from the error term. The value of these models lies not only in their ability to generate unbiased estimates of aggregate WTP for the runoff reduction program—the ultimate goal of the analysis—but also in the light they shed on how a household's willingness to pay is affected by its location and the spatial variability in water quality.

The Distance Model

Previous research has shown that distance to an environmental good is inversely related to the WTP for that good (see Bateman et al 2002). Because neighbors are (obviously) a similar distance from the shoreline while non-neighbors might not be, and distance to shore likely affects WTP, it follows that WTP will be correlated with distance.

To correct for this, we develop the Distance Model which expands equation (1) to include the inverse of distance to the Bay, 1/d, as an explanatory variable. This model matches the level of sophistication seen in recent valuation studies that estimate a distance-decay function for WTP (for example Bateman and Langford 1997; Moran 1999; Bateman et al 2000; Hanley, Schlapfer, and Spurgeon 2003). The distance measured is the Euclidean distance from the parcel centroid to the center of the nearest pixel of the bay. For bayfront properties, distance to the bay is set at zero, and so for these individuals this model is identical to the Base Model. For inland properties, it is expected that WTP will decrease as one moves further from the shoreline (the coefficient on 1/d is positive).

The Geospatial Referencing Model

The Distance Model adequately accounts for spatial correlation in respondent WTP *if* household preferences for water clarity in the Bay are defined only over the *average* water clarity in the Bay. On the other had, if household preferences are defined over the spatial arrangement of water in the Bay, *as referenced by the household's location*, then spatial correlation will persist. Just as a landscape looks different from the top of a hill than from the bottom, a household's perspective on the water clarity "topography" of Green Bay may depend on where it is located. To illustrate the spatial correlation that arises in this situation, consider that two pairs of households may the same distance from the Bay, but if the first pair is near the relatively clear north end of the Bay, and the other pair is near the relatively murky south end, we would expect the

WTP for a water clarity improvement to be more similar *within* each pair than *across* pairs.

There are many ways to correct for the spatial correlation arising from such geospatial referencing in preferences, and here we use perhaps the simplest way: we include as a variable in the WTP function the inverse of the current water clarity at the 30-by-30 meter pixel *nearest* the respondent's property, $1/q$. For bayfront properties, this is the water clarity at the point where their own property is located. For inland properties, this is the water clarity at the point with the smallest Euclidean distance from the centroid of the parcel, as measured using the analysis tools of ArcGIS.

6. Empirical Results

The survey data reveal significant differences between owners of bayfront property and owners of inland property. As presented in Table 3, bayfront property owners are generally older, more educated, and wealthier than inland property owners, and are more likely to have owned their properties longer. They are also more familiar with water clarity and algae in the Bay, and more likely to use the Bay and for recreation. Because of these differences, it is reasonable to assume that bayfront property owners have significantly different preferences for water clarity improvements, and so we estimate separate WTP functions for bayfront and inland property owners.

Table 4 presents the parameter estimates and standard errors for the three models: the Base, Distance, and Geospatial Referencing (GSR) models. Dividing all parameters by the negative of the coefficient on the offer amount *b* presents the parameter estimates and conditional expected WTP in dollar terms. For example, the Base Model predicts that all else equal, an inland property owner who sails very often (value=5) is willing to pay $\frac{.748}{.002}(5-1) = \$1496$ more for the runoff reduction program than a respondent who never sails (value=1).

As expected the marginal impact of income on E{WTP} is significantly positive for all specifications. The marginal impact of frequent sailing is positive and significant for inland owners under all specifications, and for bayfront owners in all but the GSR model. With all three models, the marginal impact of frequent hiking is positive and significant only for bayfront owners. The coefficient on the inverse distance variable is positive and significant in the GSR model, indicating WTP declines as distance from the bay increases, but surprisingly is not significant in the Distance model.

Finally, the positive and significant sign for $1/q$ in the geospatial referencing model indicates that owners living near relatively murky water are willing to pay more for a water quality improvement, all else equal, indicating that the reference location of a respondent with respect to the spatial variability of water clarity in the Bay is important to the valuation of water clarity improvements.

Expected WTP

Tables 5 reports respondent average willingness to pay—E{WTP}—for the runoff reduction program, conditional on county and property type (bayfront vs. inland), calculated using sample mean values for explanatory variables. 95% confidence intervals were derived using the Krinsky-Robb procedure (Krinsky and Robb 1986).

Several results are apparent in Table 5, and here we focus on three. First, in all models and all counties, inland respondents are willing to pay less for the runoff reduction program than are bayfront property owners. This result is expected given the negative effect of distance on WTP in the econometric results.

Second, for bayfront respondents E{WTP} is roughly the same across counties—and across models—in the Base and Distance models, but not in the GSR model, where E{WTP} is noticeably higher for Brown county than for the other counties. This exception arises because the GSR model distinguishes the WTP of respondents by the water clarity at the nearest point to the respondent's property—the referencing effect of the GSR model—and Brown County has much lower water clarity than do the other counties.

Third, this referencing effect is clearly present for inland respondents as well. E{WTP} of Brown County inland residents is much higher in the GSR model than in the Base or Distance models, whereas E{WTP} for the inland residents of the other counties is lower in the GSR model than the other models.

Aggregate WTP

The survey used in this study was designed to measure the benefits of a runoff reduction program to a household. The *annual* aggregate benefits for the program are then the sum of the WTP of each household in the study area, or

$$Agg.\,WTP = \sum_{h \in H} WTP_h \left(Z_h, d_h, q_{0h}; \alpha, \beta, \gamma \right) \tag{1}$$

where H is the set of households in the study area. Because we estimated the model separately for bayfront and inland property owners, we first aggregate over the two groups separately to get an aggregate WTP for bayfront properties and an aggregate WTP for inland properties. The total benefits equal the sum of these two numbers. The aggregate WTP for type t properties, where t = (bayfront, inland) is

$$\begin{aligned} Agg.\,WTP_t &= \sum_{h \in H_t} \left(a_t Z_h + \beta_t \frac{1}{d_h} + \gamma_t \frac{1}{q_{0h}} \right) \\ &= \left(\alpha_t \sum_{h \in H_t} Z_h + \beta_t \sum_{h \in H_t} \frac{1}{d_h} + \gamma_t \sum_{h \in H_t} \frac{1}{q_{0h}} \right) \end{aligned} \quad (2)$$

where H_t denotes the set of type t households and α_t, β_t, and γ_t are the money metric coefficient estimates from the logit estimation for type t households. Details of the aggregation approach are available in Moore (2006).

As shown in Figure 3, the Base and Distance models give fairly similar estimates of the aggregate annual benefit of the proposed water quality improvement plan: \$4.9 million for the Base Model and \$4.3 million for the Distance Model. The similarity of the estimates from these models reflects a combination of two outcomes: a) the relative unimportance (as indicted by statistical nonsignificance) of the distance measure in the Distance model; and b) the randomness of the sampling scheme for inland residents with respect to distance from the Bay. In other words, even if the distance measure were a significant factor in an individual's WTP, the omission of distance from the Base model causes biased parameter estimates but *not* a bias in the estimated *average WTP in the sample*, and so as long as the sample is random with respect to the distance variable, the

Base model would generate the same (unbiased) estimate of aggregate WTP as the Distance model.

By contrast, the GSR model is indeed sensitive to spatial location of the sampled properties. The estimated aggregate benefit under the GSR model is roughly twice that of the other two models--$9.4 million annually. This reflects outcomes that are the converse of those presented above: a) the relative importance of water clarity at the point nearest the household's property $\left(q_0\right)$ in the GSR model; and b) the nonrandomness of the sampling scheme with respect to this variable. As it turns out, the portion of the Bay with the lowest water clarity—the southern portion at the entrance of the Fox River—is also the portion with the highest nearby population density, namely Brown County and in particular the city of Green Bay, and we undersampled this densely-populated portion of the Bay.

7. Discussion and Conclusion

This article presents a unique approach to measuring the benefit of water quality improvements when water quality is spatially variable. We packaged water clarity maps of Green Bay, Lake Michigan in a stated preference survey of local households to identify the extent to which the location of a household with respect to the water clarity topography of the Bay—that is, the household's geospatial reference point—affects the value that the household places on a water clarity improvement in the Bay.

Three main results arise from the analysis. First, the spatial variability in an environmental good appears to be usefully and reliably conveyed with maps. Second, such spatial variability, and a household's particular residential location with respect to it, do indeed seem to affect the value that households place on improvements in the good. We refer to this relationship as "geospatial referencing". Third, in those situations where an environmental policy has a spatial component—for instance, a proposed improvement in water quality has a larger effect on one part of a water body than another—geospatial referencing by households can have a significant impact on the net benefit of the policy. A related methodological point is that calculations of aggregate WTP from nonrandom samples must account for geospatial referencing. In our analysis, the value placed by households on a runoff reduction program generating a 4-foot improvement in water clarity was greatest in the southern part of Green Bay, where water clarity was lowest and population highest. Accounting for this approximately doubles the estimated aggregate WTP of the program.

We believe that the stated preference approach developed here has good potential for application to other spatially-variable environmental goods. Future research to improve the approach should focus on the representation of spatial variability in the WTP function. In the present analysis the sufficient statistics for the household's geospatial referencing are the household's distance to the Bay and the water clarity at the point nearest the household's property. This implies that the household's WTP for the runoff reduction program depends on both the Bay-wide *average* effect of the runoff reduction program—in particular, the uniform 4-foot improvement in water clarity—and the clarity of the water nearest to the household. In reality, the household's valuation of water clarity may be more complex than this—it might depend on the water clarity *gradient* nearest the household, for example, or the water clarity in the murkiest part of the Bay (reflecting a max-min preference ordering), and so on. This is a complex and difficult issue that requires additional investigation.

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Table 1. Population and number of parcels in the study area, by county.

Townships located in…	Population	Total number of Parcels	Total number of residential parcels less than 35 acres, *N_parcels*	Percentage of *N_parcels* that are located on the bayfront
Door County	4,133	6,227	4,557	32.48%
Kewaunee County	1,553	1,378	838	17.18%
Brown County	125,771	50,659	40,441	1.99%
Oconto County	13,138	9,727	3,518	11.65%

Note: Population data based on January 1, 2005 estimates from Wisconsin State Government Website, http://www.doa.state.wi.us, and only includes townships within the four counties that contain bayfront property.

Table 2. Response rate by offer amount and by property type.

Offer	Number Mailed	Response Rate	Useable Response Rate
$50	167	66.7%	64.7%
$100	168	56.7%	53.5%
$300	167	65.8%	61.4%
$500	166	67.3%	63.3%
$700	166	71.2%	68.6%
$1000	166	58.1%	54.8%
Total	1000	64.3%	61.0%
Bayfront	500	69.6%	66.4%
Inland	500	58.4%	55.6%
Total	1000	64.3%	61.0%

Note: Returned but completely unanswered (unit non-response) are considered as unreturned surveys. Returned surveys with item non-response for the CV question are considered "Unusable" and left out of the analysis. "Useable" implies a returned survey with a CV response.

Table 3. Characteristics of bayfront and inland property owners.

	Bayfront	Inland
Percent of respondents who frequently boat on Green Bay.	34%	16%
Percent who frequently hike along the shore of Green Bay.	88%	73%
Average age of property owner.	59.2	53.4
Median education level.	Trade school graduate	Some college or trade school
Median income level.	\$70,000 - \$79,999	\$50,000 - \$59,999
Percent retired.	45%	30%
Average time owner has owned their property.	19.6 years	16.4 years
Percent of properties used as vacation homes.	44%	11%

Table 4. Unstandardized parameter estimates.

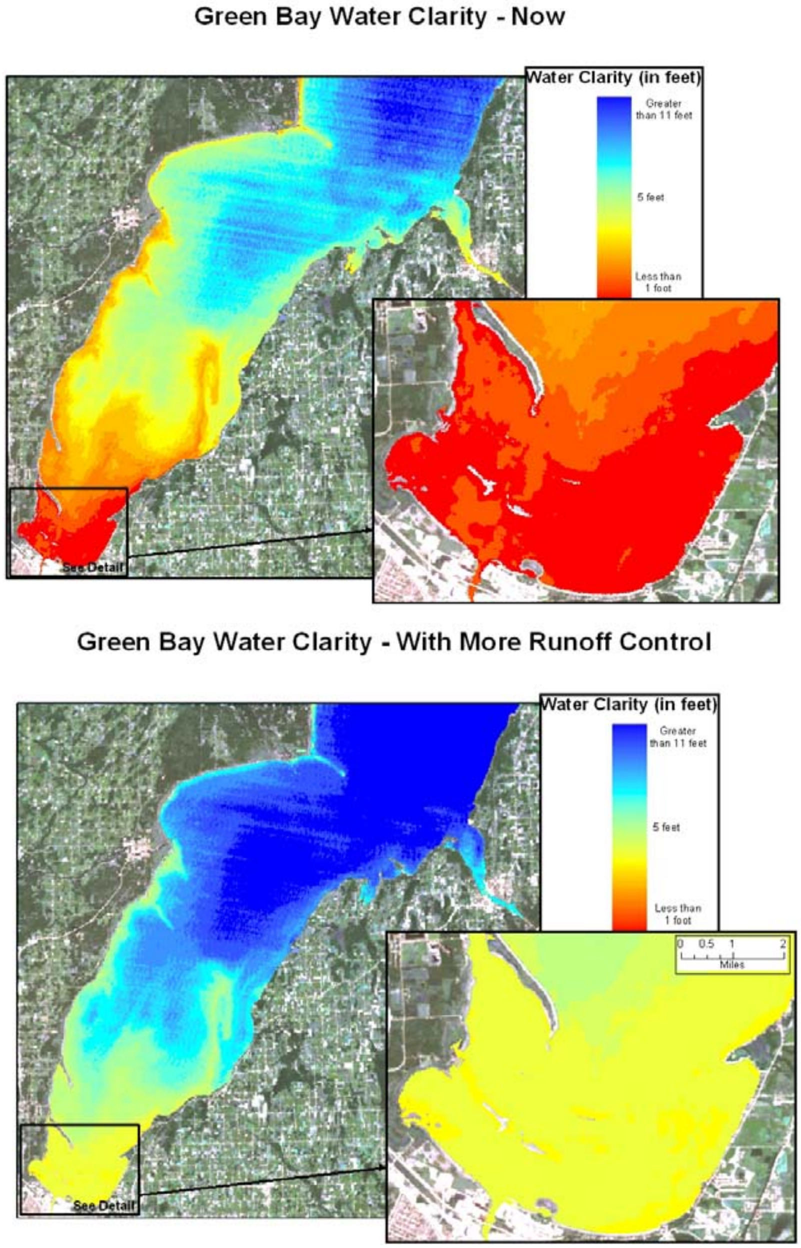
	Base Model		Distance Model		Geospatial Referencing Model	
Parameter Estimates (Std. Error)	**Bayfront**	**Inland**	**Bayfront**	**Inland**	**Bayfront**	**Inland**
Constant	-0.910* (0.503)	-1.235** (0.476)	-0.910* (0.503)	-1.158** (0.480)	-1.356** (0.544)	-1.642** (0.562)
Sailboating	0.227* (0.121)	0.748** (0.231)	0.227* (0.121)	0.681** (0.234)	0.193 (0.123)	0.684** (0.238)
Hiking	0.229** (0.109)	-0.059 (0.123)	0.229** (0.109)	-0.093 (0.126)	0.246** (0.111)	-0.053 (0.128)
Income Group (1=low, 3=high)	0.368** (0.161)	0.344* (0.176)	0.368** (0.161)	0.359** (0.178)	0.373** (0.163)	0.323* (0.180)
Inverse of shortest distance to the Bay (d^{-1})	-	-	-	0.218 (0.143)	-	0.278* (0.150)
Inverse of water clarity at nearest point, (q_0^{-1})	-	-	-	-	6.421** (2.731)	5.540* (3.180)
Offer (*b*)	-0.002** (0.0004)	-0.002** (0.0005)	-0.002** (0.0004)	-0.002** (0.0005)	-0.002** (0.0004)	-0.002** (0.0005)
-2LL	374.292	286.517	374.292	284.272	368.644	281.256

Table 5. Average WTP, by County and Respondent Type

		Base Model		Distance Model		Geospatial Referencing Model	
		Bayfront	**Inland**	**Bayfront**	**Inland**	**Bayfront**	**Inland**
Door	**E{WTP}**	409.55	92.46	409.55	124.11	320.70	57.00
	95% CI[a]	[298.15, 517.41]	[0,243.22]	[299.71, 519.35]	[0,268.25]	[178.37, 447.83]	[0, 220.38]
Kewaunee	**E{WTP}**	450.91	276.49	450.91	254.10	390.32	183.17
	95% CI	[343.49, 567.25]	[47.84, 448.44]	[343.85, 566.31]	[39.29, 417.80]	[273.92, 506.54]	[0, 365.34]
Brown	**E{WTP}**	465.49	103.79	465.49	96.80	624.32	245.71
	95% CI	[354.72, 585.98]	[0, 248.64]	[356.00, 586.62]	[0, 234.63]	[456.61, 835.72]	[0, 447.15]
Oconto	**E{WTP}**	363.37	24.14	363.37	16.19	336.25	0.00
	95% CI	[241.44, 471.47]	[0, 182.40]	[244.95, 474.92]	[0, 167.00]	[219.33, 444.40]	[0, 148.25]

[a]Calculated using the Krinsky and Robb Procedure (Krinsky and Robb 1986), with 10,000 draws of β

Figure 1. Sample water clarity maps for a property owner in the city of Green Bay, WI



Note: The actual maps used in the survey were 8.5 x 11 inches each and color coded, with a legend indexing the color to water clarity as measured by Secchi depth. Data provided by Jonathan Chipman at the Environmental Remote Sensing Center, University of Wisconsin-Madison. Details of the process used to create these data are available in Chipman et al (2005).

Figure 2. The distribution of sampled properties within the study area.

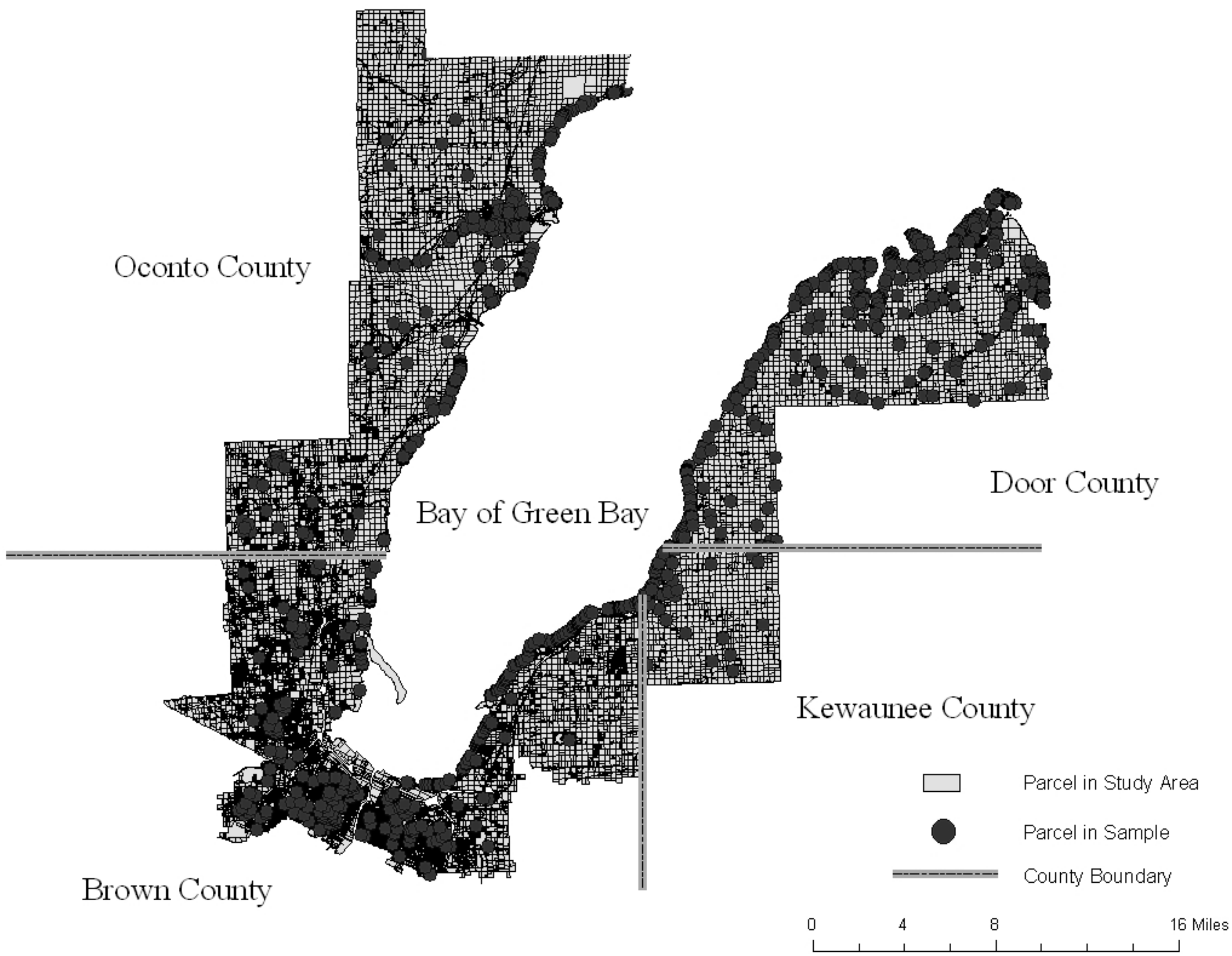
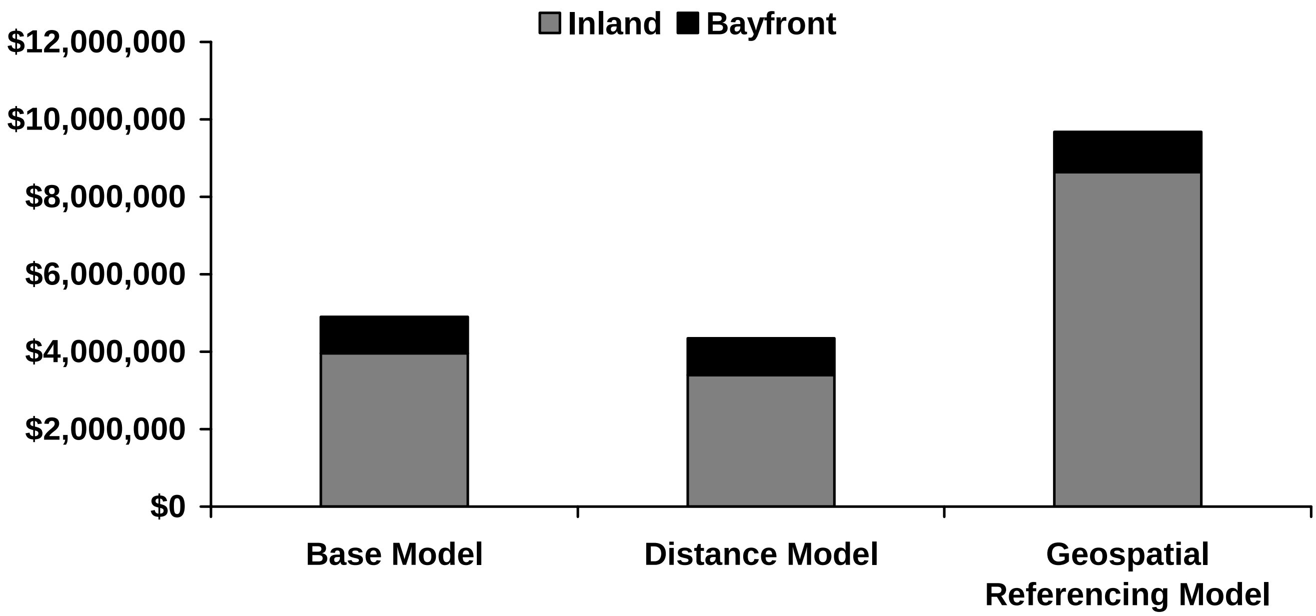


Figure 3. Aggregate WTP by property type.



Footnotes

[i] Of the 457 properties considered in the estimation, 110 were missing income data. For these individuals, the income response was imputed following Mitchell and Carson (1989). The average response, conditional on township and bayfront/inland property, was used as a proxy for this variable. All responses (observed and imputed) were then divided into three quantiles, which is the final variable used in the estimation. A similar process was used to impute the missing “Boating” and “Hiking” variables for 16 and 11 of the observations, respectively.