Valuing a Spatially Diverse Non-market Good:
The Benefits of Reduced Non-Point Source Pollution in Green Bay, WI

Rebecca Moore, Assistant Professor
Warnell School of Forestry and Natural Resources
University of Georgia
Athens, GA 30602
RMoore@warnell.uga.edu

Richard C. Bishop, Senior Consultant, Stratus Consulting
Professor Emeritus, Dept. of Agr. and Applied Economics, University of Wisconsin
2112 Regent St, Madison, WI 53726
rcbishop@wisc.edu

Bill Provencher, Professor
Department of Agricultural and Applied Economics
University of Wisconsin-Madison
427 Lorch St, Madison, WI 53706
rwproven@wisc.edu

***Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, OR, July 29-August 1, 2007***

**Abstract.**

This article presents an empirical approach to correcting for spatial interactions in stated preference data when valuing large-scale, spatially variable environmental improvements. This approach is presented in the context of a contingent valuation study estimating the benefits of reduced non-point source pollution in Green Bay, Wisconsin. The significant spatial variation of water clarity conditions in this large water body was captured using satellite-derived GIS data. This article focuses on two significant challenges: first, ensuring respondents are adequately informed of how the proposed change will impact their individual utility stream; second, dealing with the spatial effects within the estimation model. The GIS water clarity data were used to measure the initial conditions faced by each individual parcel. Including this information in the analysis significantly increased the estimated expected WTP of some individuals but decreased that of others. Some of the difference in aggregated benefits is likely due to issues of spatial correlation between properties that is unaccounted for in the simpler models.

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

Valuing improvements in water quality has long been a staple in the environmental economist's toolbox. Countless studies have relied on both revealed and stated preference methods to value water quality improvements. The variation in the details of these studies, particularly in how the water quality improvement is measured and described, is quite impressive. Some examples of quantitative measures that have been used include water level (Lansford and Jones 1995; Eisworth et al 2000), abundance of fecal coliform in the water (Leggett and Bockstael 2000) and water clarity (Poor et al 2001; Gibbs et al 2002; Boyle, Poor, and Taylor 1999).

Other studies, particularly stated preference studies, have relied on qualitative or categorical measures of water quality, with the most common approach being the water quality ladder. First developed by Vaughan (1986), and made 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).

Despite the long history of water quality valuation studies, there is little guidance in how to conduct a valuation study for a large scale environmental improvement whose magnitude varies significantly over its spatial range.  This is particularly true when stated preference methods are the preferred option. The last decade or so has seen tremendous advancement in the way environmental economists consider spatial data. In a recent review of the literature, Bateman et al (2002) identify several areas in which GIS and spatial analysis have been used to improve empirical environmental economic studies, including hedonic valuation studies and aggregating non-market values. In addition, econometric models that allow us to correct for spatial interaction among agents continue to be developed and improved (for example, see Anselin 2002). Unfortunately, these methods are not yet well developed for discrete choice models which are used to analyze stated preference data. In addition, the qualitative measures of water quality typically used in stated preference studies, including the water quality ladder, are not easily adaptable to large bodies of water in which the spatial variability of water quality and/or individual preferences is significant.

This article describes an attempt to collect and analyze stated preference data when faced with a large scale, spatially varied water quality improvement. This is presented in the context of estimating the benefits of reduced non-point source pollution in the bay of Green Bay, Wisconsin. In this article we focus on two main challenges to this type of study. One challenge involves adequately describing *to the respondents* how the proposed change will impact their individual utility stream. The other challenge requires that *the analyst* understands and correctly measures how each individual in the larger population will be affected by the change depending on their location relative to variations in the improvement.

The first challenge, creating an effective scenario design, is considered one of the most difficult challenges, yet essential components, of designing a contingent valuation

(CV) study (Mitchell and Carson 1989). In most studies, the description of the good being valued is incomplete; the survey does not completely describe both the baseline condition and the conditions that will result from the change presented (Boyle 2003). While the water quality ladder has proven to be a very useful tool for evaluating changes in water quality, significant spatial variation makes it practically impossible to verbally describe how an improvement in water quality will impact different regions in the area. We found no obvious way to adapt the water quality ladder or simple maps to address this problem.

The second challenge is to ensure the analyst properly accounts for how each individual views and values the improvement. Due to data restrictions, most water quality valuation studies use water quality data that is significantly spatially aggregated. This is problematic for several reasons. If individual respondents are valuing the impact of the pollution reduction near their property, but the water quality information used in the analysis cannot distinguish their property from the property 10 miles down the shore, there is significant potential for incorrect estimates. Even more troublesome, using spatially aggregated water quality information almost certainly correlates the values neighbors place on the improvement. Because methods for handling spatial correlation of the error terms are not well developed for discrete choice models, this spatial correlation is typically unaccounted for in the analysis which leads to biased parameter estimates and corresponding benefit estimates. This bias will be compounded when the individual willingness to pay (WTP) estimates are aggregated back to the larger population.

In this article, we use GIS data to tackle both of these challenges, in the context of water quality improvements in the bay of Green Bay, WI. The application and GIS data are described in section 2. Section 3 describes our use of GIS-based water clarity maps to individualize the scenario design in a contingent valuation (CV) survey. Section 4 suggests an empirical approach accounting for spatial effects in the survey responses and WTP data. Section 5 presents the estimation results and section 6 concludes.

**Study Area and Data Description**

Green Bay connects to Lake Michigan and separates the Door Peninsula from the rest of Wisconsin. Several rivers drain into the bay, and the watershed 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, there is a proposal to reduce runoff from all sources. The non-market and non-use benefits associated with this proposal are the focus of the application described in this article.

Though many individuals throughout the state are likely to value improved water clarity in Green Bay, 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), and is located south of Sturgeon Bay in the east and the Oconto/Marinette County boundary in the west. The decision to limit the study area was both logistically and politically based. Logistically, it was too costly to maintain a quality sample across the entire state. Limiting the study population to those closest to the resource ensures a basic familiarity with the resource which greatly simplifies the scenario design. It is also expected that these individuals have the highest values for improving the resource, all else equal. Politically, the cost of environmental cleanup is increasingly falling on local governments who must weigh the costs and benefits to their own citizens. 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). Based on the sample population, the empirical results reported in this study represent a lower bound on total benefits.

*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 with seasonal averages, using spatial averages is much less appealing. Properly accounting for the spatial variation requires water clarity data that include clarity measures at every point in the bay, which cannot be done with traditional measurements.

To address this problem, 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 meters. The Landsat images have a much higher resolution and comparing the radiance measures from these images to the MODIS-derived water clarity data results in a water clarity map with a 30-meter spatial resolution. In shallow areas, a portion of the observed radiance measured in the Landsat images is coming 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*

Digitalized parcel maps were obtained from the county land records offices in each of the four counties in the study area. Based on the parcel attributes available with these data, single family residential parcels less than 35 acres[1] located within the townships that border the bay were identified. The identification process varied by county depending on the attributes available. For example, only the Oconto County data included a residential zoning variable, in other counties this information was inferred from the ownership

[1] To reduce the probability of including erroneous values from farmers (who are more knowledgeable about runoff regulations and might be more skeptical of our general plan that would not single out agricultural runoff), we excluded the largest parcels from the study, since they are most likely to be used in agriculture.

information available. Details of this process are available in Moore (2006). Once the relevant parcels were identified, they were separated into two groups, bayfront and inland properties. Table 1 shows the population, total number of parcels, and number of parcels considered relevant to this study for each county.

**Conveying spatial variation in a stated preference study**

A mail survey of property owners in the study area was conducted to elicit values 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 poor water clarity can have on wildlife and recreation. 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.

Because of the direct link between non-point source pollution and water clarity, each property owner was provided with two maps of water clarity. These maps were generated with ArcGIS by overlaying the water clarity data described above onto Landsat images of the surrounding counties. One map showed current water clarity conditions in lower Green Bay. The second map showed the results of a four foot improvement in water clarity throughout the bay, the likely result of the proposed runoff control program. Each map included a large image of the entire study area and an inset showing a close view of water clarity near the respondent's property. An example of the two maps provided to an individual owning property in the city of Green Bay is shown in figure 1. 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[2]. 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 slightly higher rate than inland property owners (66% versus 56%, respectively) and the two counties in the

[2] While each property in the sample is located in the study area, the surveys were mailed to the property owner at the tax address, many of which were outside the study area, and even outside the state.

northern part of the study area, Door and Oconto, had higher response rates than the two counties in the south (65% versus 55%, respectively).

Including the clarity maps allowed us to present the respondent with more complete information regarding exactly how a four foot improvement in water clarity will impact those areas of the bay of interest to the individual. However, there has been some concern among researchers that individuals will not be willing to invest the time necessary to understand the additional information provided by complicated maps, and so any benefit this information might bring to the individual decision will be lost. In addition, if the maps were misunderstood by respondents, use of the maps could have unintended negative impacts on the validity of the study (Boyle 2003). To guard against this possibility, the survey booklet included a written description of the information provided in the map. To test the readability of the map, 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 to compare the map to their own observations 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 find not only do individuals understand the general information provided by the maps, but they are willing and able to process this information and relate it to prior knowledge. We do not believe that this added burden reduced our overall response rate or negatively impacted the quality of the responses received. Clearly, 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. However, given the increased availability of GIS data providing quantitative indicators of environmental quality, the scenario design challenge faced by stated preference practitioners could be eased. We present here one example of how this might be done.

**Empirical approach to accounting for spatial effects in the estimation of WTP**

The standard approach to estimating WTP for the water clarity improvement based on the survey data, would be to model WTP as a function of a vector of individual characteristics, $Z$, and a random component, $\varepsilon$, so that

$$WTP = \alpha Z + \varepsilon \tag{1.1}$$

The individual will respond “Yes” to the referendum question if her WTP exceeds the offer amount and “No” otherwise. Assuming the error component of equation (1.1) has an iid Gumble distribution across the population, this becomes a standard logit model, easily estimated by a variety of software packages. However, if the error terms in this model are correlated across observations, this model will produce biased parameter estimates. There are many reasons why individuals who own neighboring parcels would have similar preferences for improved water clarity and some of these reasons may be unspecified in the WTP function due to lack of available data. Unfortunately, this will result in spatially correlated error terms which are not easily dealt with in discrete choice models. The remainder of this section describes an empirical approach to specifying the spatially correlated components of the WTP function, thus removing them from the error term which allows for unbiased parameter estimation.

*The Distance Model*

Consider equation (1.1) as the WTP function specified in the Base Model. We contend that this specification, where WTP is only a function of the individual characteristics *Z*, almost certainly leads to spatially correlated error terms and, therefore, biased parameter estimates. Consider one neighborhood located one block away from the shoreline and another located 5 km from the shoreline. It is easy to see that average preferences for water clarity improvements would differ for these two neighborhoods. In fact, previous research has shown that distance to the 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 positively correlated across space. However, in the Base Model specification, the explanatory variables do not account for this effect. To correct for this, we develop the Distance Model which expands equation (1.1) to include the inverse of distance to bay as an explanatory variable. This model relies on the data from the digital parcel maps, but not the water clarity data, and 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 Zone and Radial Models*

While the Distance Model accounts for the spatial distribution of the population relative to the bay, it fails to take into account the spatial variation in initial water clarity conditions. The initial (before the proposed improvement) water clarity conditions in the bay range from 0.5 feet of clarity to over 11 feet of clarity. Diminishing marginal utility suggests that the WTP for a four foot improvement in water clarity should be greater for individuals facing lower initial clarity levels. Because neighboring parcels face similar viewpoints of the initial conditions, but distant parcels might not, the value of the improvement should be highly correlated among neighbors. The Base Model and Distance Model both treat the initial clarity condition as unobservable, which implies the error terms are spatially correlated. To correct for this, we use the water clarity data to identify the initial conditions for each parcel in the entire population, leaving the unobserved (error) terms uncorrelated. But what is the appropriate measure of initial conditions? We propose two general approaches and implement them at multiple scales.

The first approach relies on the specific maps that were provided to respondents. To create these maps, the near shore portion of the study area was divided in to nine zones. These zones are shown in Figure 3. Each member of the sample was assigned to the zone that included the area nearest their property. The maps provided to the individual included a map of the entire study area and an inset that showed a closer view of water clarity in their zone. For all bayfront owners and some inland owners, this inset contained their property. Other inland owners lived farther from shore and so their property was outside the area shown in the inset. These zones provide possible measures of initial conditions, $q_0$, at several scales, two of which are estimated in this article. In Zone Model 1, $q_0$ is the spatial average of the initial clarity within the individual's own zone. In Zone Model 2, the measure includes the spatial average of initial clarity within the individual's own zone and the two neighboring zones. For example, for an individual in Zone 5 the $q_0$ used in Zone Model 2 equals the average value for all pixels in Zones 4, 5, and 6. Zones 1 and 9 are located on the ends of the study area and are considered to have only one neighboring zone.

The second approach to measuring $q_0$ considers the clarity near the individual property. In Radial Model 1, $q_0$ is set equal to the value at the point in the bay nearest to the property. For bayfront properties, this is the initial water clarity at the point where their own property is located. For inland properties, the nearest point is the point on the bay with the smallest Euclidean distance from the centroid of the parcel, as measured using the analysis tools of ArcGIS. Radial Model 1 considers only the 30 meter pixel nearest the property, but it is possible that some owners, particularly inland property owners are more interested in water further from shore. To reflect this, Radial Model 2 sets $q_0$ equal to the average initial clarity for all points on the bay within a 1 km radius of the point nearest the property.

There are advantages and disadvantages to both approaches. As noted above, the Zone approach relies on the specific maps seen by the individual. Because the respondent viewed a close up of their own zone, it is possible that the information in this zone was the primary information used to make the valuation decision. In addition, because the zones run along the shoreline of the bay, this approach allows us to expand the scale of our measure to include only near shore waters in a fairly straightforward manner. However, two problems exist with this approach. First, the Zone measures are not specific to individual properties and so they do not incorporate all available spatial information. Some properties were located near the border of two zones, but could only be assigned to one zone. Second, while all Zones are equal in total area, they differ in the percent of the Zone covered in water. In some zones, the area included extends farther from shore than in other areas. With the radial approach, the value of $q_0$ is specific to each parcel and the size of the area considered is constant across parcels. However, this approach relies heavily on the location of the nearest point which may be a problem, particularly for inland property owners who are not likely to care about the water clarity within 30 m of someone else's backyard. The two approaches are not necessarily mutually exclusive and it is possible that one measure is more accurate for one group than another. The objective here is not to create an exhaustive list of all possible measures of initial conditions, or to identify the "correct" measure. It is simply to illustrate the options available given the availability of GIS data, without which, none of these measures could be calculated.

**Empirical Results**

An important observation from the survey data is the significant difference between owners of bayfront property and owners of inland property. As seen in Table 3, bayfront property owners are more likely to use the bay and shoreline for recreation, be familiar with water clarity and algae in the bay, and be older, more educated, and have higher income than inland property owners. In addition, bayfront properties tend to be owned for a longer period of time and used as vacation homes, rather than as a primary residence. Because of these differences, it is reasonable to assume that bayfront property owners have significantly different preferences for clarity improvements. To reflect this difference, we estimate separate WTP functions for the bayfront and inland property owners in our sample.

Table 4 presents the parameter estimates and standard errors for the Base Model, Distance Model, Zone Models, and Radial Models. Three individual characteristics gathered from the survey data were included in the estimation. The first indicates how often the individual goes sailboating in Green Bay and the second indicates how often the individual walks or hikes along the shoreline of Green Bay. Both of these variables were measured on a five point Likert-scale, with "1" indicating "never" and "5" indicating "very often". The third characteristic is household income, recorded as one of three income quantiles[3].

Table 4 presents the unscaled coefficient estimates from the logit model which includes the offer amount as an explanatory variable. To estimate the parameters of the WTP function, divide the coefficient on the WTP explanatory variables by the negative

[3] 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.

of the coefficient on the offer amount. For example, in the Base Model, the predicted WTP of an inland property owner is

$$
\begin{aligned}
E\{WTP \mid Z, d, q_0\} &= \hat{\alpha} Z \\
&= \frac{-1.235}{0.002} + \frac{0.748}{0.002} Sailboating + \frac{-0.059}{0.002} Hiking + \frac{0.344}{0.002} Income
\end{aligned}
\tag{1.2}
$$

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, but only significant for bayfront owners in the Base, Distance, and Radial 2 Models. Conversely, 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 under most specifications, indicating WTP decreases as distance from the bay increases. Looking at the different specifications, the impact of initial clarity conditions is less obvious, as the coefficient on this variable is significant using some measures, but negative using other measures. The implications of this result are discussed below.

*The Marginal Utility of Improved Clarity*

Due to the variation in water clarity across the sample, we can estimate the marginal utility of an improvement in water clarity for those models that include a measure of initial water clarity. Consider two property owners with identical characteristics, whose properties are equally distant from the bay. The only difference between the two owners is the initial water clarity conditions near their property. In the data, $q_0$ is measured in $1/16^{th}$ of a meter and ranges from 4 to 54, so the marginal utility of water clarity can be reasonably identified for clarity levels ranging from zero to 4 meters. If one of our two property owners faces one meter of clarity, but the other faces 1.5 meters, the value of half a meter of clarity, located one to 1.5 meters below the surface, is equal to the difference in the expected WTP of these two individuals. So the value of a marginal improvement in $q$ is simply

$$\frac{\Delta WTP}{\Delta q} = \hat{\gamma}\left(\frac{1}{q^A} - \frac{1}{q^B}\right) \tag{1.3}$$

where $\hat{\gamma}$ is the coefficient on initial water clarity divided by the negative of the coefficient on the offer amount and $q^A$ and $q^B$ are the new and old values of $q$. Using the parameter estimates given in Table 4, we can compare three aspects of marginal WTP for improved clarity.

The first comparison is between bayfront and inland property owners. According to the estimated parameter values, the WTP of inland property owners is not statistically dependent on initial water clarity levels for any of the models estimated. The marginal WTP of bayfront property owners is always greater than that of inland property owners. This implies that a given individual with property along the bayfront will have a higher WTP than an individual with the same characteristics who owns inland property, for all initial levels of water clarity. This is intuitive, as the bayfront property owner is likely to have higher use and non-use values for water clarity simply because of his more immediate and constant relationship with the water.

The second and third comparisons are related to the different measures of water clarity used in the models. Comparing the Zone Models to the Radial Models shows that the marginal WTP for an additional foot of clarity is higher for the Zone models than for the Radial models. We can also look at the effect of the scale of the water clarity measure. Zone Model 1 and Radial Model 1 both consider the water clarity in a small area relative to Zone Model 2 and Radial Model 2. The larger scale models imply a higher marginal WTP. By definition, the Zone models include a spatial extent larger than the comparable Radial measures so it is likely that the observed difference between the type of measure and the spatial extent of the measure are related. Regardless, these results indicate the impact of measurement approaches and scales in estimating the benefits of a water clarity improvement.

*Individual WTP*

Tables 5 and 6 report the E{WTP}, conditional on county and property type, calculated using sample mean data values, and a 95% confidence interval on this value, found using the Krinsky-Robb procedure (Krinsky and Robb 1986). The uncertainty expressed in the confidence interval is due to the variance of the estimated parameters. Because of the differences in mean data values for different counties, we estimated a separate value for each county. As a result, for each model, we present eight E{WTP} values, a bayfront and inland value for each of four counties. Several interesting observations can be made from these results.

First, E{WTP} varies significantly between counties for both bayfront and inland properties. For every model, owners in Oconto County have the lowest E{WTP}. This is to be expected given the rural nature of the county and the relative lack of vacation homes. Owners in Brown and Kewaunee Counties have the highest E{WTP}. These counties are more urban and located in the southern part of the bay, where water clarity is poorest.

Including distance from the bay as an observable variable increases E{WTP} for Door County owners, but decreases it for owners in the other three counties. This difference is likely due to the high density of inland homes very close to the bay in Door County. The mean distance to the bay is significantly higher than the median distance for homes in Door County. In the Base Model all properties are treated as though they are the same distance from the bay. In the Distance Model, the parameter estimates imply that WTP is lower for properties farther from the bay and higher for properties close to the bay. In Door County, the majority of properties are very close to the bay and so have a higher WTP. This drives up the mean WTP for the county. In the other counties, the mean distance to the bay is at least twice that of Door County. Also, the properties in other counties are more symmetrically distributed about their mean. This decreases the E{WTP} for these counties, relative to the base model.

Including a measure of the initial water clarity conditions also has a mixed impact on E{WTP}. Because distance was included in each of these models, the proper comparison is with the results of the Distance Model. The WTP of bayfront property owners is more dependent on initial conditions than is the WTP of inland property owners. For bayfront owners, conditioning WTP on initial conditions significantly increases the E{WTP} of Brown County properties, which are located in the southernmost part of the bay where water clarity is the poorest. The E{WTP} decreases for properties in Door and Oconto Counties, located in the northern part of the study area where initial clarity is already around 11 feet. The rationale for these differences is similar to the discussion of distance above. Assuming WTP does not depend on initial conditions, is equivalent to assuming everyone faces the same initial conditions, or that there is no correlation between initial conditions and WTP. While this might be a valid assumption for a smaller body of water, it is clearly not the case for Green Bay. We expect that property owners facing poor initial conditions will have a higher WTP for the same absolute increase in water clarity. So when we allow WTP to depend on initial conditions, we should find that the E{WTP} should increase for properties with low initial clarity and decrease for others. Both the Zone and Radial approaches show this to be generally true, however, the pattern is much more consistent and significant for bayfront properties.

**Discussion and Conclusion**

Based on the data presented in this application, it is clear that the biased parameter estimates that result from spatially correlated error terms can lead to potentially significant impacts on final WTP estimates and resulting policy recommendations. Further research is needed to compare the different measures of water clarity, as statistical comparisons of the goodness of fit of the different specifications used in this article do not aid in model selection. These future studies could use survey questions to solicit information regarding which attributes of the improvement play the largest role in the decision making process. In some ways, using water clarity maps is similar to conjoint analysis stated preference studies in which respondents choose between two bundles of different attributes, in that the attributes of the choice are unique to each individual. Unlike the conjoint analysis, though, in this study, the analyst cannot observe exactly which attributes of the good the respondent is focused on. Is near shore clarity more important that clarity in the middle of the bay? Or is the respondent most concerned about the worst levels of clarity, regardless of where they are located. Additional survey questions addressing this issue would help in model selection.

This article presents a unique approach to measuring the benefits of water quality. The size of the study area and the enormous variation in water quality throughout the bay presented major challenges to conducting a valid CV study. The issues addressed by environmental and resource economics are unavoidably dependent on space and the potential role of GIS in helping to tackle these issues is only just beginning to be explored (Bateman et al 2002). This article represents a first step at applying spatially detailed GIS water quality data to a stated preference study of water quality improvements.

The results of this article support previous work that shows WTP for water quality improvements is inversely related to the distance to the water body. Previous CV studies of water quality improvements have relied on categorical representations of water quality that do not lend themselves to valuing marginal improvements in quality. This article takes the approach of many revealed preference studies in conditioning WTP on a quantitative measure of water quality specific to each observation, allowing for direct estimation of the WTP for a marginal improvement in quality. The benefit of this approach is avoiding the unnecessary and often untrue assumptions that water quality does not vary across the study area or that individual WTP for improved water quality does not depend on the water quality currently faced by the individual.

In fact, by leaving distance and initial clarity out of the model, we cannot estimate unbiased parameter values because the error terms of the model will be spatially correlated. First consider the distance variable. If you do not include this in the model, as in the Base Model, then the error terms for inland respondents will be spatially correlated since distance information ends up in the error term. This variable is significant in the other models, suggesting spatial correlation of the error term in the Base Model. Second, consider the initial water clarity variable. If this is left out of the model, as in the Base and Distance models, then the error term for bayfront properties will be spatially correlated because water clarity is spatially correlated. This is also a significant variable, which again suggests spatial correlation of the error term in both the Base and Distance models. Spatial correlation in discrete choice models leads to biased and inefficient parameter estimates and is generally difficult to identify and correct. By using the digital water clarity and parcel data, we can identify the spatially correlated variables of distance and initial water clarity and separate these from the error term. This controls for spatially correlated errors and generates unbiased and efficient parameter estimates.

**References**

Anselin, L. (2002), "Under the hood: Issues in the specification and interpretation of spatial regression models," *Agricultural Economics* 27: 247-267.

Bateman, I., A. Jones, A. Lovett, L. Lake, and B. Day (2002), "Applying Geographical Information Systems (GIS) to Environmental and Resource Economics." *Environmental and Resource Economics* **22**(2): 219-269.

Bateman, I., I. Langford, N. Nishikawa and I. Lake (2000), "The Axford Debate revisited: a case study illustrating different approaches to aggregation of benefits data." *Journal of Environmental Planning and Management* **43**(2): 291-302.

Bateman, I., and I. Langford (1997), "Non-users WTP for a national park: an application of the contingent valuation method." *Regional Studies* **31**(6): 571-582.

Boyle, K. (2003), "Contingent Valuation in Practice." In *A Primer on Non-Market Valuation*, edited by P. Champ, K. Boyle, and T. Brown. Kluwer Academic Publishers, Boston.

Boyle, K., J. Poor, and L. Taylor (1999), "Estimating the Demand for Protecting Freshwater Lakes from Eutrophication." *American Journal of Agricultural Economics* **81**(5): 1119-1122.

Carson, R., and R. Mitchell (1993), "The Value of Clean Water: The Public's Willingness to Pay for Boatable, Fishable, and Swimmable Quality Water." *Water Resources Research* **29**(7): 2445-2454.

Chipman, J., T. Lillesand, S. Batzli, S. Peckham, and P. Wolter (2005), Satellite monitoring of Wisconsin's nearshore Lake Michigan waters. Proceedings, Annual Meeting of the American Society for Photogrammetry and Remote Sensing (ASPRS), 7-11 March 2005, Baltimore.

Dobson, S. (2004), *Introduction to Limnology.* McGraw-Hill, New York, NY.

Eiswerth, M., J. Englin, E. Fadali, and W. Shaw (2000), "The value of water levels in water-based recreation: A pooled revealed preference/contingent behavior model." *Water Resources Research* **36**(4): 1079-1086.

Gibbs, J., J. Halstead, K. Boyle, and J. Huang (2002), "An Hedonic Analysis of the Effects of Lake Water Clarity on New Hampshire Lakefront Properties." *Agricultural and Resource Economics Review* **31**(1): 39 – 46.

Hanley, N., F. Schlapfer, and J. Spurgeon (2003), "Aggregating the benefits of environmental improvements: distance-decay functions for use and non-use values." *Journal of Environmental Management* **68**(3): 297 – 304.

Heaton-Amrhein, J. and Holden, C. (2005), "Wisconsin Land and Water Conservation Annual Progress Report- 2004." WI Department of Natural Resources Publication No. ARM pub 153.

Johnston, R., E. Resedin, R. Iovanna, C. Miller, R. Wardwell, and M. Ransen (2005), "Systematic Variation in Willingness to Pay for Aquatic Resource Improvements and Implications for Benefits Transfer: A Meta-Analysis." *Canadian journal of Agricultural Economics* **53**(2-3): 221-248.

Krinsky, I., and A. Robb (1986), "On Approximating the Statistical Properties of Elasticities." *The Review of Economics and Statistics*, **86**: 715-719.

Lansford, N., Jr., and L. Jones (1995), "Recreational and Aesthetic Value of Water Using Hedonic Price Analysis." *Journal of Agricultural and Resource Economics* **20**(2):341-355.

Leggett, C. and N. Bockstael (2000), "Evidence of the Effects of Water Quality on Residential Land Prices." *Journal of Environmental Economics and Management* **39**(2): 121-144.

Magat, W., J. Huber, W. Viscusi, and J Bell (2000), "An Iterative Choice Approach to Valuing Clean Lakes, Rivers, and Streams." *Journal of Risk and Uncertainty* **21**(1):7-43.

Mitchell, R., and R. Carson (1989), *Using Surveys to Value Public Goods: The Contingent Valuation Method.* Resources for the Future, Washington, D.C.

Moore, R. (2006), "Essays in Non-Market Valuation: Innovations in Theory and Practice," Ph.D. dissertation, University of Wisconsin – Madison.

Moran, D (1999), "Benefits transfer and low flow alleviation: what lessons for environmental valuation in the UK." *Journal of Environmental Planning and Management* **42**(3): 425–436.

Poor, P.J., K. Boyle, L. Taylor, and R. Bouchard (2001), "Objective versus Subjective Measures of Water Clarity in Hedonic Property Value Models." *Land Economics* **77**(4): 482-493.

Vaughan, W. (1986), "The RFF Water Quality Ladder." In *The Use of Contingent Valuation Data for Benefit Cost Analysis in Water Pollution Control*, editted by R. Mitchell and R. Carson, Resources for the Future, Washington, DC.

Wisconsin Department of Natural Resources (2006), "Wisconsin's Priority Watershed and Priority Lakes Program." http://dnr.wi.gov/org/water/wm/nps/watershed.htm.

**Table 1. Population and number of parcels in 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 | | Zone Model 1 | | Zone Model 2 | | Radial Model 1 | | Radial Model 2 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Parameter Estimates (Std. Error)** | **Bayfront** | **Inland** | **Bayfront** | **Inland** | **Bayfront** | **Inland** | **Bayfront** | **Inland** | **Bayfront** | **Inland** | **Bayfront** | **Inland** |
| Constant | -0.910* (0.503) | -1.235** (0.476) | -0.910* (0.503) | -1.158** (0.480) | -1.300** (0.545) | -1.528** (0.538) | -1.816** (0.612) | -1.697** (0.615) | -1.356** (0.544) | -1.642** (0.562) | -1.198 (1.082) | 0.916 (1.087) |
| Sailboating | 0.227* (0.121) | 0.748** (0.231) | 0.227* (0.121) | 0.681** (0.234) | 0.196 (0.123) | 0.676** (0.238) | 0.172 (0.124) | 0.677** (0.239) | 0.193 (0.123) | 0.684** (0.238) | 0.230* (0.121) | 0.624** (0.233) |
| Hiking | 0.229** (0.109) | -0.059 (0.123) | 0.229** (0.109) | -0.093 (0.126) | 0.239** (0.110) | -0.061 (0.128) | 0.252** (0.111) | -0.055 (0.129) | 0.246** (0.111) | -0.053 (0.128) | 0.233** (0.110) | -0.052 (0.128) |
| Income Group (1=low, 3=high) | 0.368** (0.161) | 0.344* (0.176) | 0.368** (0.161) | 0.359** (0.178) | 0.377** (0.163) | 0.324* (0.180) | 0.374** (0.164) | 0.314* (0.181) | 0.373** (0.163) | 0.323* (0.180) | 0.368** (0.161) | 0.399** (0.182) |
| $d^{-1}$ | - | - | - | 0.218 (0.143) | - | 0.264* (0.148) | - | 0.263* (0.149) | - | 0.278* (0.150) | - | 0.208 (0.143) |
| $q_0^{-1}$; $q_0$ = own zone | - | - | - | - | 8.218** (4.104) | 6.220 (3.834) | - | - | - | - | - | - |
| $q_0^{-1}$; $q_0$ = own and nearest zones | - | - | - | - | - | - | 20.858** (7.671) | 11.670 (8.081) | - | - | - | - |
| $q_0^{-1}$; $q_0$ = nearest point | - | - | - | - | - | - | - | - | 6.421** (2.731) | 5.540* (3.180) | - | - |
| $q_0^{-1}$; $q_0$ = nearest 1 km radius | - | - | - | - | - | - | - | - | - | - | 12.230 (32.443) | 98.564** (46.853) |
| Offer | -0.002** (0.0004) | -0.002** (0.0005) | -0.002** (0.0004) | -0.002** (0.0005) | -0.002** (0.0004) | -0.002** (0.0005) | -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 | 370.203 | 281.658 | 366.736 | 282.188 | 368.644 | 281.256 | 374.150 | 279.438 |

Note: $d$ is measured in kilometers and $q_0$ is measured as 1/16 meters. Asterisk (*) and double asterisk (**) denote variables significant at 10% and 5% respectively.

**Table 5. Individual WTP for Bayfront Property Owners by county**

| | | Base Model | Distance Model | Zone Model 1 | Zone Model 2 | Radial Model 1 | Radial Model 2 |
|---|---|---|---|---|---|---|---|
| Door | E{WTP} | 409.55 | 409.55 | 341.13 | 288.45 | 320.70 | 408.96 |
| | 95% CI[a] | [298.15, 517.41] | [299.71, 519.35] | [213.96, 473.94] | [144.59, 425.53] | [178.37, 447.83] | [203.35, 599.97] |
| Kewaunee | E{WTP} | 450.91 | 450.91 | 464.51 | 562.61 | 390.32 | 451.85 |
| | 95% CI | [343.49, 567.25] | [343.85, 566.31] | [366.79, 587.05] | [435.56, 719.88] | [273.92, 506.54] | [259.95, 633.37] |
| Brown | E{WTP} | 465.49 | 465.49 | 586.78 | 640.59 | 624.32 | 465.73 |
| | 95% CI | [354.72, 585.98] | [356.00, 586.62] | [428.87, 779.21] | [477.82, 846.60] | [456.61, 835.72] | [270.60, 652.71] |
| Oconto | E{WTP} | 363.37 | 363.37 | 326.36 | 328.20 | 336.25 | 364.26 |
| | 95% CI | [241.44, 471.47] | [244.95, 474.92] | [203.52, 440.70] | [206.22, 438.03] | [219.33, 444.40] | [138.18, 557.81] |

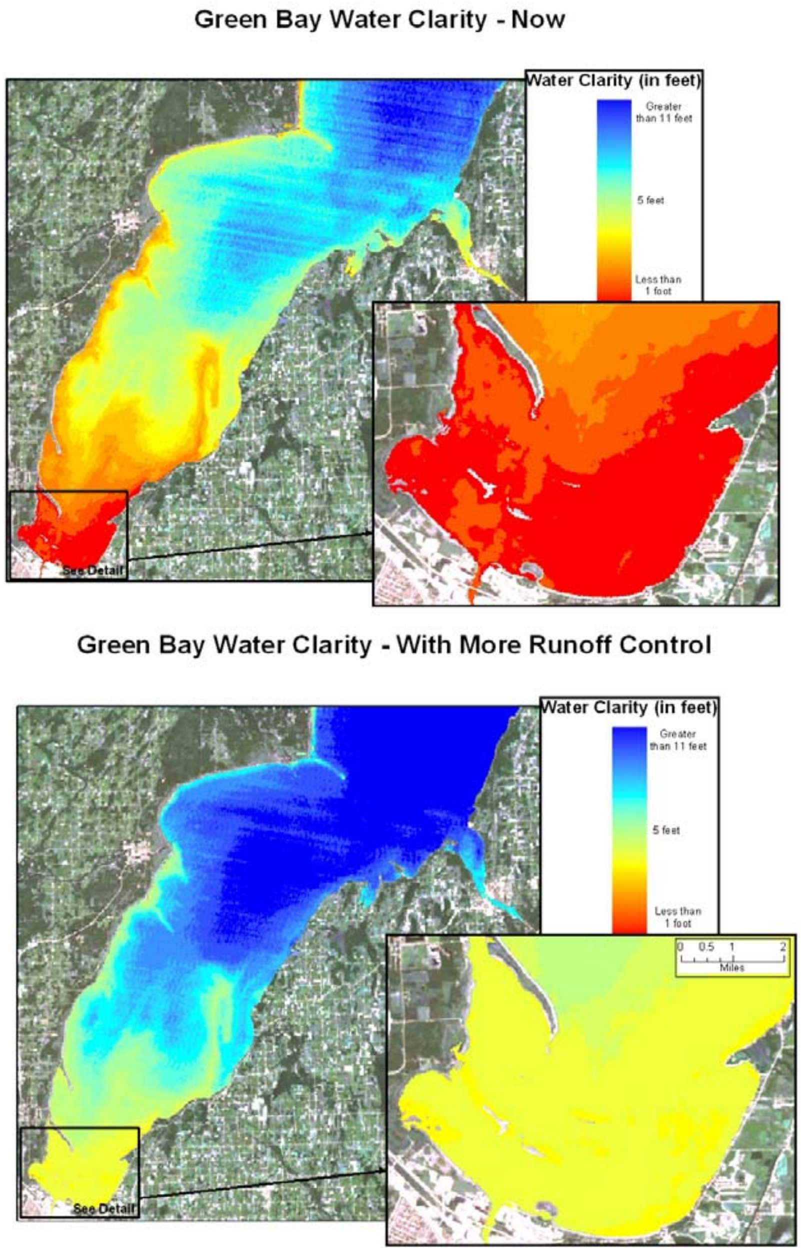
[a]Calculated using the Krinsky and Robb Procedure (Krinsky and Robb 1986), with 10,000 draws of $\beta$

**Table 6. Individual WTP for Inland Property Owners by county**

| | | Base Model | Distance Model | Zone Model 1 | Zone Model 2 | Radial Model 1 | Radial Model 2 |
|---|---|---|---|---|---|---|---|
| Door | E{WTP} | 92.46 | 124.11 | 66.37 | 61.85 | 57.00 | 101.46 |
| | 95% CI[a] | [0,243.22] | [0,268.25] | [0,223.64] | [0, 236.07] | [0, 220.38] | [0, 248.25] |
| Kewaunee | E{WTP} | 276.49 | 254.10 | 244.40 | 323.10 | 183.17 | 203.58 |
| | 95% CI | [47.84, 448.44] | [39.29, 417.80] | [19.72, 401.47] | [86.43, 498.64] | [0, 365.34] | [0, 373.79] |
| Brown | E{WTP} | 103.79 | 96.80 | 242.53 | 221.26 | 245.71 | 109.01 |
| | 95% CI | [0, 248.64] | [0, 234.63] | [0, 438.65] | [0, 417.82] | [0, 447.15] | [0, 243.31] |
| Oconto | E{WTP} | 24.14 | 16.19 | 0.00 | 0.00 | 0.00 | 24.08 |
| | 95% CI | [0, 182.40] | [0, 167.00] | [0, 141.70] | [0, 146.89] | [0, 148.25] | [0, 174.25] |

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

**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 in color and were created using water clarity data provided by Jonathan Chipman at the Environmental Remote Sensing Center, University of Wisconsin-Madison. Details of the process used to create that data are available in Chipman et al (2005).

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

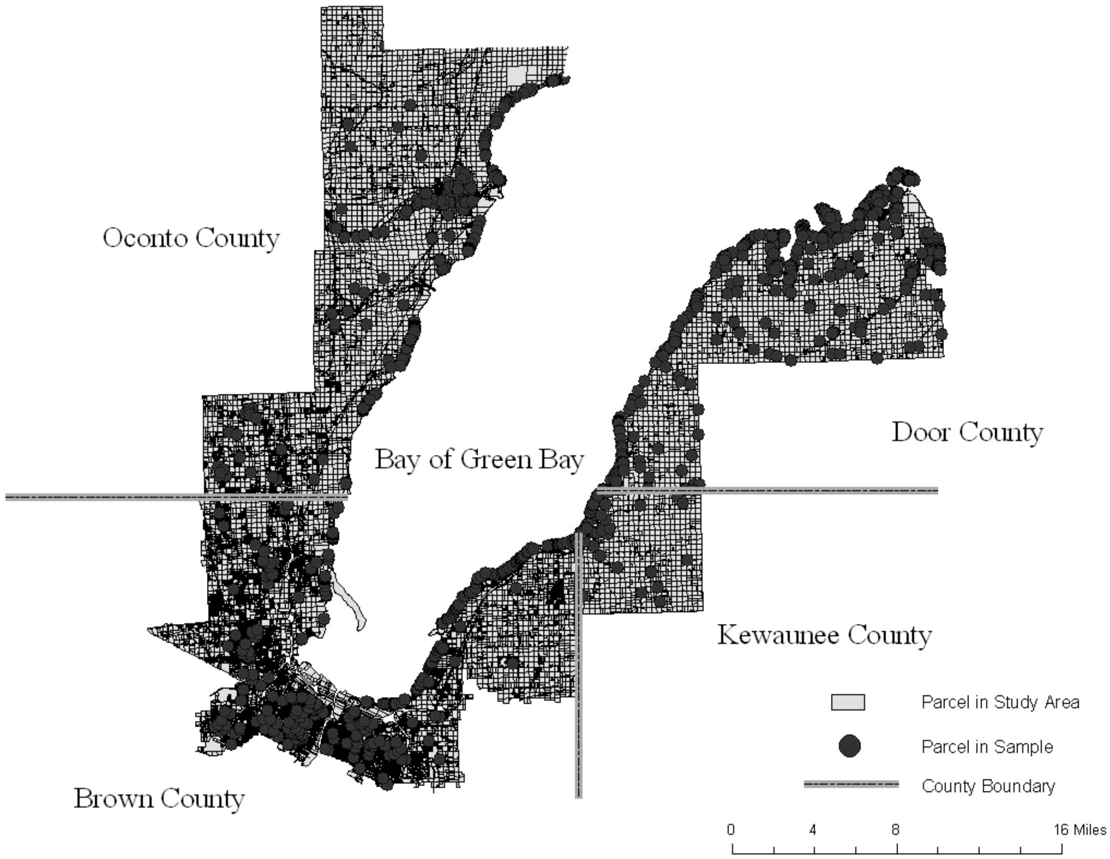


**Figure 3. Boundaries of the zones used for the Zone Models.**