THE INFLUENCE OF WATER QUALITY ON THE HOUSING PRICE AROUND LAKE ERIE

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Abstract

The primary objective of this paper is to estimate the influence of Lake Erie water quality on the housing price by taking spatial effects into account. The robust LM tests for spatial autocorrelation suggested that spatial error model specification is more likely model in our study. Fecal coliform counts and Secchi depth disk reading are used as water quality measures. In order to overcome the spatio-temporal aspects of Secchi depth disk reading data, Kriging was used for spatial prediction. We found the significant influences of both water quality measures on housing values. Gradient effects considering the distance from a beach and water quality variables are also observed.

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1. Introduction

Lake Erie is one of the five large freshwater lakes in North America and 13th largest natural lake in the world. The pace of residential and commercial development around the shoreline of Lake Erie increased considerably following substantial improvements in the lake's water quality and clarity in the 1970's and 1980's. Between 1982 and 1997, the amount of urban land use in the eight Ohio counties bordering Lake Erie increased 24.4 percent, an increase of 112,500 acres. A significant portion of this development appears tied to Lake Erie. For example, the amount of urban development in Ottawa County, a county that contains a number of lake amenities and recreational sites, increased 53 percent during this fifteen year time period. In this research we focus on the linkage between lake quality and residential development and how the lake and the amenities influence the demand for residential housing.

There have been several hedonic price studies linking housing price and water quality since 1960s. Epp and Al-Ani (1979) incorporated water pH and perceived water quality and concluded a one-point increase in pH would result in $653.96 (1972 $s) increase in the mean sales value of the properties. Young (1984) included one to ten water quality ratings by local officials. The study showed that the values of the properties adjacent to the bay were an average of $4,700 less than equivalent properties. Steinnes (1992) studied fifty-three Minnesota lakes by using secchi depth disk readings as his water quality measure and found that each additional foot of clarity would raise the value of a lot by $206. Michael, Boyle and Bouchard (1996) used secchi depth disk readings of minimum clarity for thirty-four Maine lakes and found that a one-meter improvement in lake clarity would increase property prices by anywhere from $11 to $200 per foot frontage. Leggett and Bockstael (2000) employed inverse distance-weighted average of fecal coliform counts as water quality measure and controlled for emitter effects by including straight-line distance to the nearest sewage treatment plant to investigate the influence of water quality on residential property values along the Chesapeake Bay coastline. They found that a change of 100 fecal coliform count /100 mL resulted in a change in property prices of about 1.5 percent.

Among the studies mentioned above, only Leggett and Bockstael (2000) took the presence of spatial autocorrelation into account. The number of hedonic studies involving water quality itself is small comparing to air-quality studies. Hedonic studies with water quality considering spatial effects are very limited. We consider the spatial aspects in our model and also try to overcome the difficulty of handling water quality data (especially Secchi depth readings) collected over different points in space and time.

2. Hedonic Pricing Models

General hedonic pricing models employ different functional forms to estimate the effects of independent variables (housing structures, neighborhood environments, proximity to places, other variables of interests such as environmental variables and crime rate on property values. General form is expressed as

$$\mathbf{P} = \mathbf{P}(\mathbf{H}, \mathbf{N}, \mathbf{D}, \mathbf{E})$$

where $\mathbf{P}$ is the sales price of a house, $\mathbf{H}$ is structural and property characteristics of the house, such as lot sizes and the age of the house, $\mathbf{N}$ represents neighborhood characteristics, such as median income and ranking of schools, $\mathbf{D}$ is proximity to places, such as proximity to cities and beaches, and $\mathbf{E}$ represents environmental variables.

Whenever we deal with properties which locate within a certain distance together in one model, we should consider general intrinsic spatial relationships among them. More specifically, we should handle spatial dependence and spatial heterogeneity. Spatial dependence or spatial autocorrelation implies a lack of independence across observations in cross-sectional, spatially organized data. Anselin and Bera (1998) define spatial autocorrelation as

> … the coincidence of value similarity with locational similarity. In other words, high or low values for a random variable tend to cluster in space (positive spatial autocorrelation), … The existence of positive spatial autocorrelation implies that a sample contains less information than an uncorrelated counterpart. In order to properly carry out statistical inference, this loss of information must be explicitly acknowledged in estimation and diagnostics tests.

Tobler's (1979) *first law of geography* states that "everything is related to everything else, but close things more so". We have to determine a relevant "neighborhood set" indicating which locations have interaction by defining spatial weights matrix. "Neighbors" have been defined in different ways. Weight matrix based on distance decay with a cutoff distance or *k-nearest* neighbor are often used in recent studies

The general model of spatial hedonic model is specified as follows:

$$
\begin{aligned}
&P = \rho WP + X\beta + \varepsilon \\
&\varepsilon = \lambda M\varepsilon + \mu \\
&\mu \sim N(0, \sigma^2 I)
\end{aligned}
$$

where P is property sales price, X is NxK matrix including structural and property characteristics of the house, neighborhood characteristics, proximity to places, environmental variables or other variables of interests, β is Kx1 vector of coefficients, W and M are spatial weights matrices, ρ and λ are coefficients on spatially lagged dependent variables P and ε, ε is a Nx1 spatial autoregressive error, and μ is a Nx1 random error term with variance $\sigma^2 I$. It is not necessary for W and M to be different.

Spatial lag model is expressed as follows:

$$P = \rho WP + X\beta + \varepsilon$$

where ε is assumed to be a vector of independent and identically distributed (i.i.d) error terms. When spatial lag model is selected, we know that a housing price is explained partially by the neighboring observations. In other words, this model is capturing spillover effects of neighborhood. The modeler is interested in measuring the strength of the relationship and the "true" effect of the explanatory variables after removing the spatial autocorrelation effects. The weight matrix is constructed to reflect the structure of potential spatial interactions among observations (Kim *et. al*.,2003). When the spatial autoregressive parameter, ρ is tested to be significant, ordinary least square (OLS) estimates are biased and inconsistent (Kelejian and Prucha, 1998). Therefore, we have to use maximum likelihood estimation or instrumental variables estimation for this model (Anselin (1988), Kelijian and Prucha (1998), Kelijian and Prucha (1999)).

When ρ is tested insignificant and λ is significantly different from zero, we employ spatial error model which is expressed as follows:

$$P = X\beta + \varepsilon$$
$$\varepsilon = \lambda M\varepsilon + \mu$$

where μ is an N x 1 vector assumed to be distributed i.i.d. normal. The housing price is a function of the omitted variables at neighboring location as well as the independent variables. This model is appropriate when there is no theoretical or apparent spatial interaction between any house and its neighboring observations and the modeler is interested only in correcting the potentially biasing influence of spatial autocorrelation by using data with spatial features. OLS estimates are unbiased, but inefficient.

3. Data

Deed transaction data between 1991 and 1996 in four Ohio counties along Lake Erie, Erie, Lorain, Ottawa and Sandusky, are included. After excluding records with missing variables, 10,665 observations are used in our analysis.

3.1. Water Quality Measure

In this study, fecal coliform counts and secchi disk depth readings are used as the measurement of water quality. Fecal coliform counts data have been obtained from the Ohio Department of Health and Erie County Health Department. Secchi depth readings have been provided by the Ohio Department of Natural Resources and Stone Laboratory of the Ohio State University. Fecal coliform counts measured in 18 beaches in four counties, Cuyahoga, Lorain, Erie, and Ottawa, have been used. The data are generally collected weekly between May to September every year. We first determine the closest beach to each house, and then assign the aggregated fecal coliform value over the previous year of the house purchase.

Secchi depth reading is an indicator of water clarity. It is measured by dropping a black and white disk tied to a rope and recording the length of the rope at the point the disk is not visible any more. Therefore, the larger the reading value is the better the water clarity is. The readings are taken between May and October in typical years. They are not taken from the same spots every month or year. Since the data varies over both space and time, using the raw data causes massive amount of missing observations. In this study, we used ordinary spherical Kriging as our spatial interpolation method. Kriging makes inferences on unobserved values, takes into account the covariance structure as a function of distance and obtains the best linear unbiased predictor. Kriging is done with all the data points taken each year and has been assigned to 18 beaches. Each house which is allocated to a beach based on the distance to the beach is given secchi disk depth readings value from the previous year of the house purchase. ArcMap is used for the implementation of Kriging. An example of Kriging is shown in Figure 1.

3.2. Housing, Proximity and Neighbourhood Data

Deed Transaction Data for 1991 – 1996 was provided by the Center for Urban and Regional Analysis (CURA), the Ohio State University. Based on the addresses on the data set, we geocoded the location of each house, assigned to each census block and determined each school district. School district ranking was obtained from the Ohio Department of Education. Proximities to the closest beach from each house and Sandusky City were calculated with road network distance. Population density and total number of crimes were adopted from census block group level data. School district ranking was recalculated for four counties along the Lake shore based on the ranking in Ohio State. In this paper, we are going to present the results from four combined counties, Lorain, Erie, Sandusky and Ottawa.

4. Estimation of Hedonic Pricing Models

Table 1 is the list of dependent and independent variables we included in the hedonic regression. Since the hedonic price function is the locus of equilibrium points, there is little a priori information to determine the functional form. Four functional forms, linear, semi-log, inverse semi-log and log-log form are estimated. We found that inverse semi-log and log-log form have unacceptably high conditional number indicating multicollinearity, therefore we excluded them from our candidate specifications. Based on the fitness of the model, semi-log form which has the highest R squares and acceptable condition number is adapted for further analysis and is reported in this paper.

The expected signs for LOTACR, BLDGSF, BATHN, GRGSQF, AIRCND, DECK, FIREPL, SECCHI1, DISTFECAL and DISTSECCHI are positive. For Secchi depth reading, since the greater the reading the better the water clarity, we expect a positive sign. DISTFECAL DISTSECCHI is included to evaluate the gradient effects of water quality variables. Interaction between fecal coliform counts and distance to the closest beach is included as FECAL1 multiplied by DISTBEACH while it is SECCHI1 over DISTBEACH for the interaction of water clarity and the distance to the beach in order to match the direction of the effects to the housing price. The impact of age of a house may have quadratic form since a very old house tends to have historic values. Therefore we also include AGE2 which is AGE squared and expect it to have positive sign.

Negative signs are expected for AGE, TOTCRIME, SDRANK4, DISTBEACH and FECAL1. For school district ranking, since the highest ranking is the first, we expect that the lower the actual rank value is (which indicates that the rank is higher), the higher the housing price is. The distance to the closest beach is expected to have a negative impact on the housing price because we expect that people prefer living closer to the beach.

Fecal coliform counts have a negative impact on the housing price since we assume that the higher the bacterial counts is the lower the housing values are. As for PDENS and SANDUSKYCITY, there are no a priori signs expected. Population density could have either effect. The effect of the proximity to Sandusky City is uncertain because people could have different preference on living close to a city.

4.1. Estimated Results of the OLS Regressions

The results of the semi log model estimated using ordinary least squares are reported in the second column of Table 2. All the variables except for proximity to Sandusky City are statistically significant at least at 10 percent level with expected signs. All of the housing characteristics are estimated as being statistically significant at 1 percent level. The age of a house has an impact with quadratic form on housing price. Based on the estimated coefficients on age, we found that a house being older than 83.5 years old has positive value on its housing price. Negative and significant result on population density value reveals house owner’s preference for living in a less crowded area. Negative influence of the number of crimes is as expected. Proximity to Sandusky City is not significant while the distance to the closest beach has negative and significant impact on the housing price. This indicates that home owners prefer living closer to the beach.

Fecal coliform counts have negative and significant influence on the housing value while secchi disk depth readings have positive and significant impact. Therefore, we confirmed that water quality of the Lake do influence the housing price in these counties. The interaction terms of water quality variables with distance to the closest beach is significant at 10 percent for fecal and less than 1 percent level for secchi disk depth readings. This result indicates that there is strong evidence that water quality effects decay as the house locates farther away from the closest beach. This evidence is stronger for secchi disk depth readings according to the level of significance. Since water clarity can be observed not only at the beach but also anywhere near the coastline, distance from the beach matters significantly for this measure. On the other hand, fecal coliform is typically observed on a beach as beach closing or consequences of bacterial outbreak such as unpleasant odor, or from the information provided by the Department of Health, therefore we could conclude that the distance to the beach has less influence on the variable.

4.2. Estimated Results of Spatial Error Model

The results of robust Lagrange multiplier (LM) tests for spatial dependence are highly significant (Anselin, 1988). Since the significance levels indicate that spatial error model is more likely alternative, we are going to report the result of spatial error model. Highly significant result of Jarque-Bera test on normality of errors suggests that the estimation with maximum likelihood method is not appropriate. Therefore, we use generalized method of moment to estimate the spatial error model (Kelejian and Prucha, 1998).

GEODA is used for the generation of spatial weight matrix and MATLAB is used for the estimation of the spatial error model. After the experimentation of several different weight matrices, we found that the weight including neighbours within 150 meter radius of a house returns the best outcome in terms of the fit of the model. The matrix is formed by measuring distances between houses within 150 meter radius of each other, taking the reciprocal of each distance, and normalizing the sum of distances for each house to 1. The estimated results of semi-log specifications are shown in the third column of Table 2.

The significance level of spatial autoregressive coefficients indicates the existence of omitted variables with spatial structures in the neighbourhood. The levels of significance do not change significantly between OLS and spatial error model except for SANDUSKYCITY variable. Now proximity to Sandusky City is negative and statistically significant at 5 percent level, meaning that home owners prefer to live closer to Sandusky City. As for AGE variable, we found that the influence of the house age changes from negative to positive at 83 years, which is a slight decrease compared to the OLS result.

Based on the estimated coefficients both from OLS and spatial error model, marginal implicit prices are computed and shown in Table 3. Average values of each variable are given in the second column of the table. Third column shows marginal implicit price computed based on OLS estimates and the fourth column is marginal implicit price from spatial error model. Marginal implicit prices are calculated by multiplying the estimated coefficients by the mean price. As for DISTBEACH, FECAL1 and SECCHI1, interaction terms are taken into account and computed accordingly by involving mean values of each variable. Comparisons of the absolute magnitudes of computed marginal implicit prices between OLS and spatial error model reveal an interesting tendency. As for housing structure variables except for air-conditioning dummy, marginal implicit prices are larger for OLS while for neighbourhood, proximity and environmental variables, results from spatial error model are larger. Therefore, we can conclude that we overestimate housing structures and underestimate variables involving spatial structures if we do not correct for spatial error autocorrelation.

As for the variables of our main interests, FECAL and SECCHI, we found that one count increase in fecal coliform count decreases housing value by 1.94 dollars while one centimeter increase in water clarity increases housing value by 21.54 dollars when measured at the mean distance to the beach. A change in 100 fecal coliform counts per 100 mL is estimated to produce a 0.17 percent change in housing value. This value is far smaller if we compare the outcome of Leggett and Bockstael who found a 1.5 percent change in property value for the same change in fecal coliform counts. One possible reason for the difference could be due to the disparity of mean fecal coliform counts. While mean fecal coliform count in our study is 255 counts per 100 mL, it is 103 counts per 100 mL for their study. Since the original condition is more than twice better in Leggett and Bockstael study, the impact from the same change in fecal coliform counts is also larger. As for secchi disk depth readings, a 100 centimeter or 1 meter change in water clarity causes a 1.93 percent change in housing value.

There is an inverse relationship between the magnitude of these values and the distance from the closest beach. For example, if we compute the influence of water quality at one kilometer from the assigned beach for each house, the benefit from the one unit decrease in fecal coliform counts is 3.23 dollars while it is 26.87 dollars for water clarity. As we see in OLS estimates, the interaction terms are significant at 10 percent level for fecal coliform counts and 1 percent for secchi disk depth readings. We also found that secchi interaction term gives consistent result when we test various model specifications and the use of different weight matrices while the interaction term for fecal coliform counts does not become significant even at 10 percent level for some specifications. Therefore, we can conclude that there is stronger evidence of the gradient effect for water clarity.

4.3. Average Net Benefit for Each Beach

If the amenity change is localized and the number of houses affected by the change in the amenity is small, the hedonic function itself can provide an approximate measure of welfare gains. Therefore, given the estimated results of both OLS and spatial error model, we computed the average change in welfare or net benefit based on two hypothetical scenarios. We consider the hypothetical scenario of fecal coliform counts being improved to the level of 200 counts per 100 mL and of secchi depth readings being increased to 200 centimeter for each beach. Houses which are not affected by the improvement are excluded from the calculation.

Table 4 summarizes the average net benefit calculation per house. The first column shows the names of counties where each beach is located and the second column lists names of the beaches. The third column is the average net benefit per affected house when fecal coliform counts decreased to 200 counts per 100 mL and the fourth column is for the increase in secchi depth readings to 200 cm. Unobserved values are due to the fact that initial water quality on the beach is better than the targeted level in the scenario. The lowest welfare gain from the change in fecal coliform counts observed is for Rye Beach, $ 88 while the highest is $ 2692 for East Harbor State Park. As for secchi disk depth readings, the lowest net benefit is $ 221 of Lakeside Beach and the highest is $ 2379 of Rye Beach.

5. Conclusions

We analyzed the influence of water quality on housing values by using deed transaction data from four counties along Lake Erie in Ohio. 10,665 observations were involved in this study. We first ran the ordinary least squares with semi-log functional form which was chosen based on the goodness of fit after excluding the inappropriate specifications due to high multicollinearity. The robust Lagrange Multiplier tests for spatial autocorrelation suggested that spatial error model specification is the more likely model in our case. We incorporated two water quality variables, fecal coliform counts and secchi disk depth readings, to observe the influence of water quality on house price together with housing structure variable, neighborhood variables and proximity variables. By comparing the estimated coefficients from OLS and spatial error model, we found that OLS estimates tend to overestimate housing structures while underestimating neighborhood, proximity and environmental variables. We also found that one count increase in fecal coliform counts decreases housing values by 1.94 dollars while one centimeter increase in water clarity increases the housing value by 21.54 dollars. Interaction terms included in the model confirmed the gradient effects of water quality depending on the distance from the beach. As the distance from the beach increases, the influence of water quality decays. The evidence of the gradient effect is stronger for the water clarity measure.

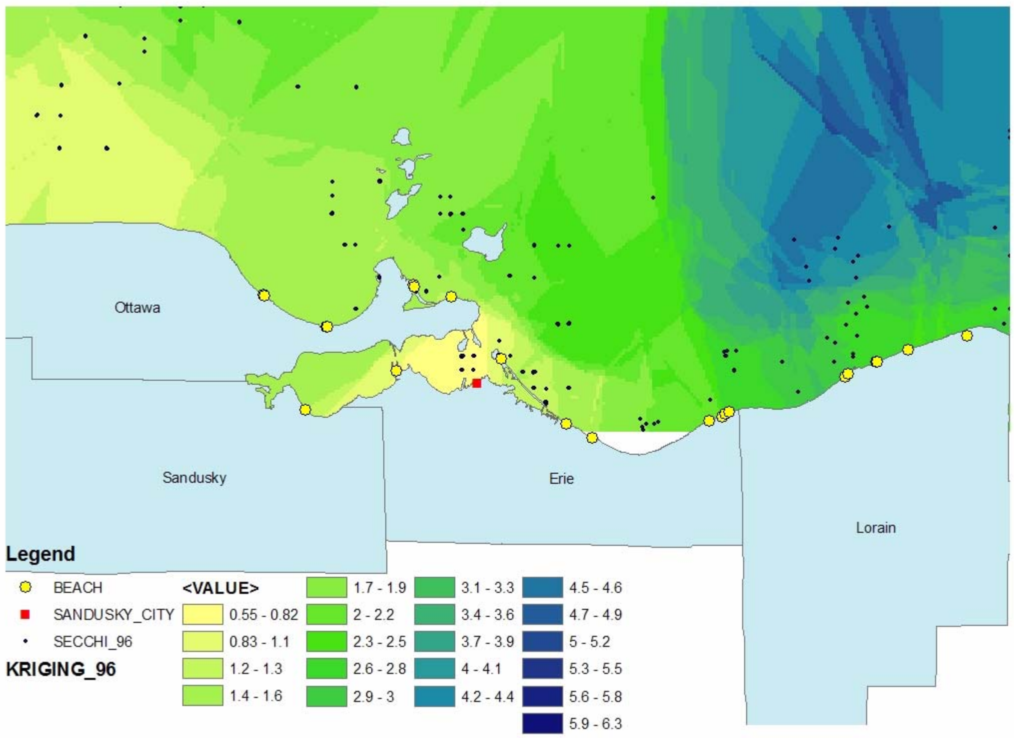

Figure 1. Example of Kriging, Year 1996

Table1. Variables and Descriptive Statistics

Variable	Description	Units	Min	Max	Mean	Std.Dev.
DPRICE	Discounted housing price in 1996 dollars	$	50,000.00	669,291.96	111,503.16	59,186.36
LOTACR	Lot acreage	acre	10.00	78,000.00	586.72	1,806.78
BLDGSF	Building square foot	sq.ft.	196.00	5,824.00	1,649.75	5.88
BATHN	Number of Bathrooms		1.00	5.00	1.42	0.01
GRGSQF	Garage square foot	sq.ft.	0.00	4,040.00	133.30	2.27
AGE	Age of the house (built year - year of purchased)	year	0.00	171.00	30.38	0.24
AIRCNDD	= 1 if there is air-conditioning system		0.00	1.00	0.75	0.00
DECK	= 1 if there is a deck		0.00	1.00	0.10	0.00
FIREPL	= 1 if there is a fireplace		0.00	1.00	0.47	0.00
PDENS	Population density		33.48	13,900.00	2,420.25	21.91
TOTCRIME	Total number of crime within a census block group		3.00	186.00	42.56	0.34
SDRANK4	School district ranking within 4 counties along the Lake shore		1.00	38.00	19.53	0.12
SANDUSKYCITY	Proximity to Sandusky city	km	0.29	571,599.36	53.60	0.18
DISTBEACH	Total network distance to the closest beach	km	0.01	48.13	12.56	0.08
FECAL1	Fecal coliform counts, previous year of the house purchase	counts per 100ml	12.00	2,717.26	255.99	2.73
SECCHI1	Secchi depth readings, previous year of the house purchase	cm	89.54	431.78	221.27	0.70
DISTFECAL1	= DISTBEACH*FECAL1		0.75	88,629.47	3,222.18	54.62
DISTSECCHI1	=(1/DISTBEACH)*SECCHI1		2.80	18,728.29	52.50	2.36

Table2. Estimated Results of OLS and Spatial Error Model

	OLS			ERROR		
DEPENDENT	LNDPRICE	t-value		LNDPRICE	t-value	
CONST	10.9975	(638.745)	***	11.0754	(605.04)	***
LOTACR	0.000013	(9.849)	***	0.000013	(10.12)	***
BLDGSF	0.00033	(63.033)	***	0.0003	(57.71)	***
BATHN	0.0735	(13.388)	***	0.0652	(12.36)	***
GRGSQF	0.000055	(4.249)	***	0.000026	(2.09)	**
AGE	-0.0060	(-21.542)	***	-0.0060	(-20.37)	***
AGE2	0.000036	(14.236)	***	0.000036	(13.68)	***
AIRCND	0.1144	(16.025)	***	0.1168	(16.66)	***
DECK	0.0763	(10.126)	***	0.0738	(10.29)	***
PDENS	0.000019	(-15.322)	***	-0.000021	(-13.9)	***
TOTCRIME	-0.0003	(-3.457)	***	-0.0005	(-4.68)	***
SDRANK4	-0.0037	(-14.708)	***	-0.0034	(-11.35)	***
SANDUSKYCITY	-0.0001	(-.913)		-0.0004	(-1.96)	**
DISTBEACH	-0.0045	(-12.093)	***	-0.0045	(-10.81)	***
FECAL1	-0.000029	(-2.28)	**	-0.000030	(-2.33)	**
SECCHI1	0.0002	(5.481)	***	0.0002	(5.98)	***
DISTFECAL1	0.000001	(1.924)	*	0.000001	(1.81)	*
DISTSECCHI1	0.0001	(7.361)	***	0.0001	(5.13)	***
RHO				0.2691	(27.64)	***
N	10665			10665		
R^2adj	0.711			0.737		
sigma^2	0.054			0.049		

Table3. Marginal Implicit Prices

	AVE_FULL	MIP(OLS)	MIP(ERROR)
DPRICE	111503.16		
LOTACR	586.72	1.45	1.45
BLDGSF	1649.75	36.24	33.45
BATHN	1.42	8191.80	7270.12
GRGSQF	133.30	6.13	2.90
AGE	30.38	-426.01	-421.33
AIRCND	0.75	12751.72	13023.68
DECK	0.10	8507.36	8226.93
FIREPL	0.47	12442.86	10807.44
PDENS	2420.25	-2.12	-2.34
TOTCRIME	42.56	-34.34	-55.97
SDRANK4	19.53	-409.66	-376.43
SANDUSKYCITY	53.60	-16.06	-39.36
DISTBEACH	12.56	-460.1523	-467.8739
FECAL1	255.99	-1.83	-1.94
SECCHI1	221.27	20.92	21.54

Table 4. Average Net Benefit from Hypothetical Scenario

COUNTY	BEACH	FECAL ($)	SECCHI($)
LORAIN	Avon Lake	402	720
ERIE	BayView East	-	1441
ERIE	BayView West	-	1376
ERIE	Bluebird Beach	-	1538
OTTAWA	Camp Perry	1709	1073
ERIE	Cedar Point Chaussee	-	883
LORAIN	Century Park	249	863
OTTAWA	East Harbor St. Park	2692	235
CUYAHOGA	Huntington Reservation	201	670
ERIE	Huron City Beach	-	-
OTTAWA	Lakeside	-	221
LORAIN	Lakeview Park	474	792
OTTAWA	Port Clinton	1913	789
ERIE	Rye Beach	88	2379
LORAIN	Sheffield Lake Comm. Park	490	918
ERIE	Sherod Park Beach	251	1561
ERIE	Vermilion City Beach	1526	533
ERIE	Vermilion Lagoon Beach	-	1517

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