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Valuation of Water Level: A Spatial Hedonic Analysis on Lakeshore Properties

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White Bear Lake, Minnesota, has lost a large amount of water due to excessive groundwater extraction. Using a general nested spatial hedonic pricing model, this paper identifies and evaluates the impact of water loss in the lake on lakeshore properties. In addition to providing a quantitative estimate of property value loss, the results show that the marginal loss intensifies as water level persistently declines further. The findings of this study alert emerging urban areas to the negative externalities of failing to balance the tasks of meeting increased water demand as well as achieving sustainable water use.

Key words: groundwater overuse, nonmarket valuation, SARAR model, spatial econometrics, White Bear Lake

Introduction

White Bear Lake is one of the largest and deepest lakes in the Twin Cities (Minneapoli–St. Paul) Metropolitan Area of Minnesota. Despite near-average precipitation levels, the water level in the lake started to decline in 2003 due to excessive groundwater extraction in nearby counties. Over the following decade, the lake lost almost a quarter of its volume. The shrinking lake has caused various environmental and economic damages to surrounding communities, but some of these damages are difficult to measure due to their nonmarket nature. This paper uses a revealed preference method to quantify the impact of a shrinking lake embedded in the value loss of lakeshore properties.

White Bear Lake is located in northeastern Ramsey County and western Washington County (see Figure 1). Along the lakeshore are the cities of White Bear Lake, Birchwood, Mahtomedi, and Dellwood, and the township of White Bear. The lake is home to a variety of fish and plant populations thanks to its clear water. The watershed of White Bear Lake is dominated by urban lands with areas of forest, pasture, and croplands. The land along the shoreline is mainly used for residential and commercial properties as well as some private and municipal beaches.

Over the past 2 decades, the lake experienced the lowest water levels ever recorded. Figure 2 shows the historical water levels in White Bear Lake since January 1995, collected by Minnesota Department of Natural Resources (DNR). According to data from the DNR, the lake water reached a record low of 918.4 feet on January 10, 2013, more than 6 feet below the ordinary high water level (OHWL) of 924.89 feet.[1] Since then, the lake has had some rebounds during summers due to mild temperatures and regular rainfalls, but the recovery has been quite slow.

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[1] Ordinary high water level "means the boundary of water basins, watercourses, public waters, and public waters wetlands, and . . . is an elevation delineating the highest water level that has been maintained for a sufficient period of time to leave evidence upon the landscape, commonly the point where the natural vegetation changes from predominantly aquatic to predominantly terrestrial. . . " (Minnesota Statutes 103G.005, Subd. 14).

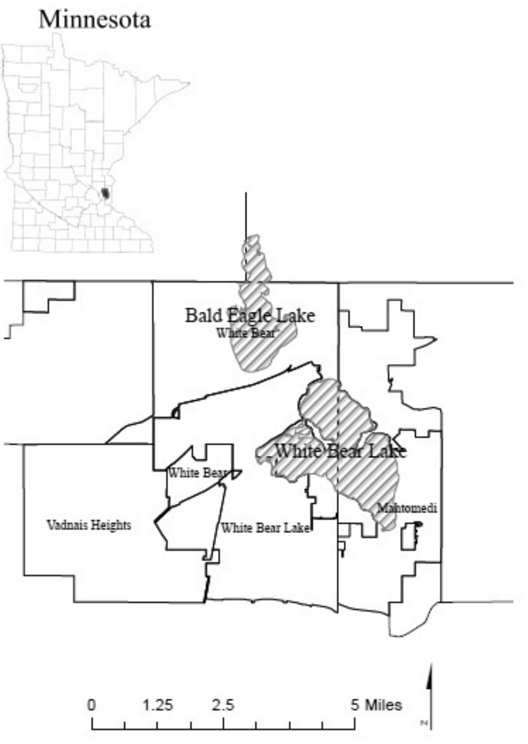

Figure 1. White Bear Lake, Minnesota

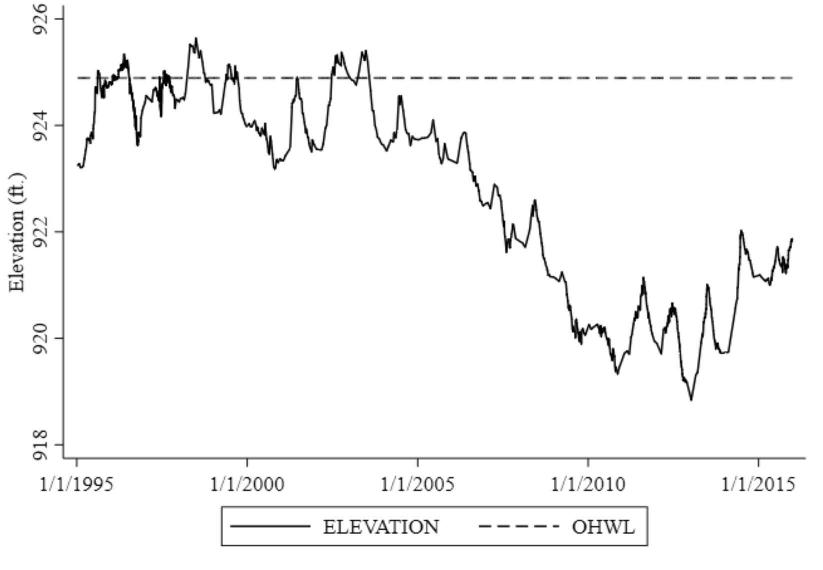

Figure 2. Historical Water Levels in White Bear Lake, 1995–2015

Source: Minnesota Department of Natural Resources (https://www.dnr.state.mn.us/lakefind/showlevel.html?id=82016700).

The shrinking of White Bear Lake has negatively affected surrounding communities. The lake was used extensively for recreation, including fishing, boating, swimming and other water activities, but such activities were restricted during periods of severe water loss. The receding water level at the lake exposed hundreds of feet of shoreline, which provided a favorable environment for invasive species, such as weeds and rodents. In addition, a large public beach located along the northwest shore of the lake (Ramsey County Beach), was closed in 2008 as a result of low water. It was reopened in June 2017 when the lake water reached a threshold of 923 feet, but the swimming area was limited to wading. The low water level also affected lakeshore businesses and lakefront property owners. Commercial marina docks had to be extended by several hundred feet to reach the water, lakefront properties lost lake view and water access, docks and boatlifts were nowhere near the shore, and the sales of retailers and restaurants in the area slowed.

The U.S. Geological Survey (USGS), in cooperation with several public agencies and private organizations, conducted a study in 2011 to characterize groundwater and surface water interactions near White Bear Lake. They discovered that White Bear Lake is extremely sensitive to water-level variations because of its unique hydrogeological features. They also found that White Bear Lake is uniquely connected to the Prairie du Chien–Jordan aquifer. As a regional groundwater resource, this aquifer experienced doubled groundwater withdrawals from 1980 to 2010 due to urban expansion and increased activities in the nearby Ramsey and Washington Counties, which led the lake water to discharge into the aquifer to replenish the groundwater (Jones et al., 2013). This finding motivated concerned residents and advocates to take legal actions. In 2012, the White Bear Lake Restoration Association and the White Bear Lake Homeowners Association filed a lawsuit against the Minnesota Department of Natural Resources for allowing excessive municipal groundwater pumping in Prairie du Chien–Jordan aquifer, causing the dramatic water-level decline in White Bear Lake.

Given the long-lasting impact of water loss in White Bear Lake, it would be useful to quantify the resulting monetary loss. Providing an estimate of the lost value by applying a spatial hedonic pricing model to property value is the primary goal of this paper. The valuation technique can reveal a wide range of use values that consumers place on a sustainably high water level in White Bear Lake, such as lake view and easy access to water. However, the value estimate does not necessarily include all the recreational benefits, especially those from visitors, nor does it account for nonuse values.

Literature

Lakes, rivers, and other water resources provide valuable environmental services, such as aesthetic views and shoreline anchoring to homeowners, opportunities of boating and fishing to nearby residents, and natural habitats for a variety of wildlife. The quality and quantity of these services may largely depend on various attributes (e.g., accessibility, water quality, views) of the water body. While these benefits, derived from the whole water body or a specific attribute, are clearly of great importance, their value can be difficult to quantify because of the nontradable feature of these environmental services. A number of nonmarket valuation techniques have been developed to estimate the implicit value of such environmental goods. The most frequently used include the hedonic method, which determines the value of a particular environmental attribute that is reflected in residential property value, and the contingent valuation method, which relies on surveys to elicit people's willingness to pay for the attribute as an estimate of both use and nonuse value.

In the literature of water resource evaluation, proximity—measured by the distance from a property to the water body of interest—has been a basic water attribute used for hedonic studies. Being close to water may generate various benefits to homeowners (e.g., better views, convenient access). The general finding is that property value falls with increasing distance from water (Brown and Pollakowski, 1977; Lansford and Jones, 1995a,b; Mahan, Polasky, and Adams, 2000; Loomis and Feldman, 2003). Besides proximity to water, economists have shown interests in evaluating water quality or clarity. For instance, Michael, Boyle, and Bouchard (2000) and Poor et al. (2001)

both find that the clarity of lake water has a positive and significant impact on the properties surrounding the lakes in their studies. In spite of the difficulty of measuring water quality and its lack of variation, several other studies have also reached the consensus that better water quality significantly increases the value of lakefront properties (e.g. Michael, Boyle, and Bouchard, 2000; Boyle, Poor, and Taylor, 1999; Leggett and Bockstael, 2000; Poor et al., 2001; Gibbs et al., 2002; Poor, Pessagno, and Paul, 2007; Artell, 2014).

This study is particularly interested in valuing the water level in White Bear Lake, Minnesota. The overall quality of the environmental services provided by the lake has significantly deteriorated as a result of continuous water loss. However, the academic literature on evaluation of water level in a water resource is relatively thin. One possible explanation is that natural water bodies like lakes and rivers may not experience significant water-level fluctuations on their own. Nonetheless, some studies have captured episodes of drawdown of lakes and reservoirs in various locations and have tried to measure the potential impact of water drawdown on the value of surrounding properties or economic activities to a larger extent. Kashian (2008) and Kashian, Walker, and Winden (2016) examine the impact of a mandatory 2-inch drawdown of Lake Koshkonong, Wisconsin, in 1991. Using a hedonic method, Kashian (2008) shows that the drawdown reduced residential property values by 8.5%, while Kashian, Walker, and Winden (2016) compare Lake Koshkonong with three other lakes that are not subject to the drawdown and find that property values surrounding Lake Koshkonong experienced less appreciation over a period of 16 years after the drawdown. Murray et al. (2003) estimate the economic impact of a hypothetical 2-month delay of the annual drawdown in Lake Douglas and Lake Cherokee and find that should drawdowns be delayed, property values would moderately increase and that $5.4 million in new spending by nonresidents would take place within the multi-county lake region. According to Allen et al. (2010), the low water level in Hartwell Lake on the Georgia–South Carolina border from 2007 to 2008 led to a 3.4% reduction in property value and a loss of $18.8 million in regional economic activities.

There are also studies that rely on the ordinary fluctuations of water levels in public lakes to examine the potential economic impacts. Lansford and Jones (1995a,b) study Lake Travis and Lake Austin in Texas and find that maintaining a higher water level in Lake Travis adds value to homes surrounding the lake, while no significant effect is observed for Lake Austin due to the lack of variation in its water level. Loomis and Feldman (2003) estimate the residential economic benefits from maintaining a high and stable water level in Lake Almanor, California and reveal that a 5% increase in the exposed shoreline (due to lower water level) would reduce property values by 1%. Using a time series regression, Rogers, Saginor, and Jithitikulchai (2014) find that the water level in Lake Conroe, Texas, has a negative curvilinear relationship with economic activities, measured by the tax revenue of major retail sectors.

Finally, Cordell and Bergstrom (1993), Fadali and Shaw (1998), Hatch and Hanson (2001), and several other studies use the contingent valuation method to estimate the recreational value associated with a high and stable water level in various lakes. Estimated willingness to pay varies, but all studies find that maintaining high lake levels brings significant recreational benefits—such as fishing, visitation, and other water activities—to nearby residents.

This study examines the influence of persistent water loss in White Bear Lake on nearby residential property values using a spatial hedonic pricing model and carefully isolates the water-level effect from other forces that potentially affect the property value. A spatial autoregressive model with spatial autoregressive errors (SARAR) is employed to accommodate potential spatial correlation in the housing market. Using a rich dataset that links Geographic Information System (GIS) housing transactions with the recorded elevations in the lake, this study is able to quantify the marginal loss in property value associated with the lowest water level on record. As environmental amenities are frequently negatively affected by urban expansion, such an estimate sheds light on water management issues facing the Minnesota Twin Cities Metro Area and other emerging regional economies. Last, this study complements the literature on evaluation of water resources with spatial hedonic techniques.

Data

This study focuses on the area within a 1-mile buffer of White Bear Lake, including the northeastern shore of Ramsey County and the western shore of Washington County. Housing information and transaction data come from MetroGIS Collaborative (2016), a regional geographic information systems initiative that collects and organizes commonly used geospatial data for the Minneapolis–St. Paul Metropolitan Area (i.e., MetroGIS Regional Parcel Dataset). The parcel dataset contains information on all properties in each of counties of the the Minneapolis-St. Paul metropolitan area, including ownership, structure, tax information, most recent transaction date (month and year), sale value, and exact location. Using this dataset, residential properties that are located within 1 mile of White Bear Lake and have been sold in the recent 2 decades are identified. These properties are distributed among ten lakeshore cities (e.g., White Bear Lake, White Bear Township, Mahtomedi) and two school districts: White Bear Lake Independent School District (ISD) and Mahtomedi ISD. The study area is close to Bald Eagle Lake, a smaller lake located to the northwest of White Bear Lake (see Figure 1). For identification purposes, a sample of properties located within 1 mile of Bald Eagle Lake is also extracted from the MetroGIS dataset. A total of 4,611 properties are included in the two samples; the most recent sale dates of these properties span from 1995 to 2015, distributed relatively evenly over the 21-year period. The recorded sale price of each property is converted to the real price, measured in December 2014 dollars using the national Consumer Price Index.

A set of structural, neighborhood, and environmental variables for each property in the dataset is collected from various sources. Housing structural attributes, recorded in the MetroGIS Regional Parcel Dataset, include living area in square feet; the presence of basement, garage, and cooling system; and lot size in acres. The age of each property at the time of sale is calculated using the date of the most recent sale and the year built. In addition to the city and school district in which each property is located, Euclidean distance from each property to the nearest highway and whether the property is located within 1.25 miles of Century College are included.[2] As suggested in previous studies (e.g. Sander and Polasky, 2009), amenities such as highways and schools are expected to significantly affect property values. These distances are calculated using the coordinates of properties and publicaly available GIS data on highway and colleges.[3]

The environmental variables associated with the lakes include the Euclidean distances of each property to White Bear Lake and Bald Eagle Lake and the water level in White Bear Lake at the time of the sale. Historical records of water level in White Bear Lake are obtained from the Minnesota Department of Natural Resources. The lake elevation has been recorded every few days, year-round since January 1924. These elevation records are used to calculate an average reading for each month, which is then matched with each property in the sample by its sale month and year. If a property is sold in a month that does not have an exact match in the water-level records, the elevation on the closest day to the sale month is used. Table 1 presents summary statistics for the two samples.

Methodology

Why Spatial Analysis?

The hedonic method has been widely used in environmental economics literature to elicit consumers' marginal willingness to pay for a particular environmental amenity embedded in property value. The basic premise of the hedonic method is that the value of a property is determined by its own characteristics as well as those of its surroundings, and the goal is to estimate the extent to which each characteristic affects the property's value. In a standard hedonic model, the log of the real sale value of a property is specified as a linear function of a set of housing structural variables,

[2] Century College is a 2-year community and technical college in the city of White Bear Lake.

[3] The highway GIS data are from the Ramsey County Surveyor's Office, and the college GIS data are from the Survey Division of Washington County Public Works.

Table 1. Summary Statistics

Variable	White Bear Lake Mean ($n = 3,578$)	Bald Eagle Lake Mean ($n = 1,033$)
Real sale price (in December 2014 dollars)	296,274.100 (221,633.900)	304,008.000 (144,560.200)
Living area (square ft)	1,590.688 (776.097)	1,869.518 (694.015)
Garage (=1 if present, 0 otherwise)	0.935 (0.247)	0.986 (0.116)
Basement (=1 if present, 0 otherwise)	0.982 (0.132)	0.980 (0.141)
Cooling (=1 if present, 0 otherwise)	0.078 (0.269)	0.004 (0.062)
Age (years)	43.448 (28.125)	22.816 (21.741)
Lot size (acres)	0.158 (0.212)	0.335 (0.357)
Distance to the nearest highway (miles)	1.942 (0.688)	1.590 (0.924)
College (=1 if within 1.25 miles, 0 otherwise)	0.190 (0.393)	0.000 (0.000)
White Bear Lake ISD	0.564 (0.496)	1.000 (0.000)
Mahtomedi ISD	0.436 (0.496)	0.000 (0.000)
Distance to White Bear Lake (miles)	0.489 (0.271)	1.885 (0.604)
Distance to Bald Eagle Lake (miles)	2.944 (1.024)	0.508 (0.286)
White Bear Lake level at month of sale (ft)	922.545 (2.004)	922.749 (1.953)
Deviation of White Bear Lake level from ordinary high water level at month of sale (ft)	−2.345 (2.004)	−2.141 (1.953)

Notes: Standard deviations are in parentheses.

neighborhood variables, and environmental attributes:

$$\ln P = \boldsymbol{X\beta} + \varepsilon, \tag{1}$$

where P indicates property value, $\boldsymbol{X}$ is a vector of hedonic covariates, and ε is an *i.i.d.* error.

This basic hedonic model fails to address the potential spatial dependence in housing prices which leads to a violation of the *i.i.d.* assumption on the error term ε. It is commonly observed that property value is not independent, but rather spatially correlated. Such spatial dependence arises if housing prices are correlated for reasons other than sharing similar (or spatially correlated) characteristics (Bell and Bockstael, 2000). For instance, the value of nearby properties often serves as a signal or price guidance for buyers and sellers in real estate transactions. This type of spatial dependence can be addressed by incorporating a spatially lagged dependent variable into the above hedonic model. The other common reason for spatial dependence in the housing market is omitting spatially correlated variables. Even after including various housing characteristics, there may still be other unobserved factors that contribute to housing value but are left uncontrolled for. If those omitted variables are spatially correlated, they are absorbed into the errors, causing the errors to be spatially correlated, making a spatially correlated error structure necessary.[4]

Ignoring spatial dependence in property values (in the form of a spatially lagged dependent variable or a spatially correlated error structure) when present results in a misspecified model and ultimately leads to biased and inconsistent estimates (Anselin, 1998). Spatial fixed effects and locational variables can be introduced into the linear hedonic model, but these attributes are not always observable and can be difficult to identify. Previous studies have shown that even after adding control variables for certain locational characteristics, spatial dependence can still remain (Baumont and Legros, 2009; Pace, Barry, and Sirmans, 1998). Moreover, Anselin and Arribas-Bel (2013) demonstrate that the removal of spatial autocorrelation by spatial fixed effects may be spurious when spatial lag or spatial error dependence exists. In addition, empirical studies have shown that allowing for unobserved spatial effects can significantly improve the accuracy of parameter estimates and the prediction of housing prices. Pace, Barry, and Sirmans (1998) review a number of spatial applications on the real estate market and conclude that employing a spatial statistical estimator provides better predictions and inferences than OLS. Baumont and Legros (2009) examine the spatial effects in housing prices in the Paris Metropolitan Area and conclude that spatial models can better control for spatial effects than a hedonic housing price model that includes neighborhood attributes. Osland (2010) demonstrates that spatial hedonic models have significantly higher explanatory power than conventional hedonic models.

Testing for Spatial Correlation

The linear hedonic model in equation (1) faces two potential sources of spatial dependence. One is in the dependent variable (i.e., the direct spatial dependence in property value), which could arise from the valuation process in real estate transactions, as previously discussed. The other source lies in omitting spatially correlated variables. In either case, the error term ε will suffer from spatial correlation, leading to biased coefficient estimates. While the housing market in White Bear Lake area is likely subject to both sources of spatial correlation, it is necessary to test their statistical significance.

Moran's I test is a common first step to detect spatial autocorrelation. This test statistic measures the level of clustering in the residuals after regressing the baseline hedonic model in equation (1). The value of the test statistic ranges from -1 to $+1$ but can be transformed to a z-score to evaluate the statistical significance of the test statistic. The null hypothesis of Moran's I test is the absence of clustering in some geographical areas (i.e., no spatial autocorrelation). A large z-score of the Maron's I statistic would suggest rejection of the null hypothesis.

[4] If the omitted variables are correlated with other explanatory variables, then the ordinary least squares (OLS) estimates will be further subject to omitted variable bias.

Table 2. Spatial Diagnostics

	Binary Weights		Inverse Distance Weights	
Test	**Statistic**	***p*-value**	**Statistic**	***p*-value**
Moran's I	45.166	0.000	45.850	0.000
Spatial lag				
Lagrange multiplier (LM)	452.487	0.000	856.216	0.000
Robust Lagrange Multiplier (RLM)	166.117	0.000	264.150	0.000
Spatial error				
Lagrange multiplier (LM)	1235.792	0.000	1634.926	0.000
Robust Lagrange Multiplier (RLM)	949.423	0.000	1042.861	0.000

An exogenous spatial weight matrix, $\boldsymbol{W}$, which captures the neighborhood structure, is crucial for Moran's I test and other spatial testing and modeling. In particular, the specification of the spatial weight matrix defines the neighboring structure and the weight given to each neighbor. Distance-based spatial weights are more commonly seen in housing market analysis as distances between houses can be calculated easily. Although there are several types of distance-based weight matrices, this study uses the "radial distance" weight matrix.[5] With this type of weight matrix, a threshold distance is chosen and housing units within the threshold distance are assumed to have spatial influence on a given property. The weights given to the defined neighbors can be binary or decay as distance increases.

As shown below, the weight matrix $\boldsymbol{W}$ consists of individual spatial weight, w_{ij}, that reflects the spatial influence of the value of house j on that of house i. If house j is located within the threshold distance of house i, 740 meters in this case, then $w_{ij} = 1$ in a binary weight matrix, or $w_{ij} = 1/d_{ij}$ in an inverse distance weight structure (i.e., the weight equals the inverted distance between houses i and j, thus less weight is given to neighbors farther away), where d_{ij} is the Euclidean distance between houses i and j. Houses located beyond the threshold distance are given a weight of 0. Diagonal elements of the matrix w_{ii} are set equal to 0 to prevent a property from being defined as a neighbor to itself. In general, the weights in a distance-based weight matrix are row standardized to ensure the total weight for each house sums to 1. Row standardization leads to a convenient interpretation of spatial parameters as measures of spatial dependence. It is also worth noting that due to row standardization, more weights are given to observations with relatively fewer neighbors; therefore, the weight matrix may not be symmetric (i.e., the weight of house i on house j is not necessarily the same as the weight of house j on house i).

$$\boldsymbol{W} = \begin{pmatrix} 0 & w_{1,2} & \cdots & w_{1,n} \\ w_{2,1} & 0 & \cdots & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n,1} & w_{n,2} & \cdots & 0 \end{pmatrix} \tag{2}$$

Table 2 presents the z-scores and p values of Moran's I test using a binary weight matrix and an inverse distance matrix. In both cases, the null hypothesis is rejected, indicating the presence of spatial autocorrelation in the residuals of the hedonic model.

After Moran's I test shows evidence of spatial dependence in the data, Lagrange multiplier (LM) tests are frequently used to determine the source of spatial dependence. Two main variants of the LM tests are the LM lag statistic test and the LM error statistic test. While both tests can detect spatial correlation in the hedonic errors, the former tests whether the correlation is due to the spatially

[5] The other commonly used distance-based matrix is the "k-nearest neighbor" weight matrix, which assumes spatial autocorrelation between any given house and its k nearest neighbors.

correlated dependent variable (i.e., spatial endogeneity), assuming no spatially autocorrelated errors, while the latter tests whether the errors are spatially autocorrelated, assuming dependent variables are not. Since neither the LM lag test nor the LM error test can exclude the possibility of the other source of spatial dependence, both tests are performed. A supplement to each of these LM tests is the robust test (i.e., robust LM lag or robust LM error), which corrects for the presence of local spatial dependence in the dependent variable or the error respectively (Florax and Nijkamp, 2003). The LM tests provide a basis for choosing an appropriate spatial model. The significance of the LM lag tests points to incorporating a spatial lag term, while significance of the LM error tests suggests including a spatial error structure.

Table 2 reports the results of the LM tests. All test statistics are highly significant, implying that substantial spatial autocorrelation exists in both the dependent variable and the errors.[6] These test results not only justify the need for spatial modeling but also provide important guidance for model selection: To adequately accommodate the spatial dependence in the data, a spatial model that can address both sources of spatial correlation is needed.

The Spatial Hedonic Model

Spatial dependence can be addressed in two distinct ways depending on the source of spatial correlation: including a spatially lagged dependent variable or specifying a spatially correlated error structure. The former is referred to as a spatial lag (SAR) model, formulated by incorporating a spatial lag ($W \ln P$) as an additional explanatory variable into the hedonic pricing model. This model is appropriate if the spatial dependence is primarily driven by the direct correlations in the dependent variable. The latter, known as a spatial error model (SEM), concerns the spatial dependence driven by autocorrelation in the error term and is specified with a spatial autoregressive error structure.[7]

Since the spatial diagnostic tests provide evidence of significant spatial dependence in both the dependent variable and the errors, a general spatial model, also known as spatial autoregressive model with spatial autoregressive disturbances (Kelejian and Prucha, 1998) is employed:

$$\ln P = \rho \boldsymbol{W} \ln P + \boldsymbol{X\beta} + \varepsilon, \tag{3}$$

$$\varepsilon = \lambda \boldsymbol{W} \varepsilon + u. \tag{4}$$

As previously defined, $\boldsymbol{W}$ is the $n \times n$ exogenous spatial weight matrix that specifies the assumed spatial relationship among properties. The parameter ρ is known as the spatial dependence parameter, which measures the degree of value dependency between neighboring houses. λ measures the spatial correlation in the error ε, and u is the *i.i.d.* error.

This model appears to be a combination of the SAR and the SEM models because both sources of spatial correlation are allowed. As in the SAR model, a significant estimate of ρ indicates the presence of an adjacency effect (i.e., the value of a house depends on the value of its neighbors), while a significant estimate of λ is considered evidence for spatially correlated errors, as in the SEM. The advantage of this general spatial model lies in its high degree of flexibility. If either λ or ρ is insignificant, the spatial process reduces to SAR or SEM, respectively. In the extreme case, where both parameters are insignificant, the SARAR model collapses to a basic hedonic model.

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[6] All spatial diagnostic tests are performed using the "spatdiag" module in Stata.

[7] Formally, the spatial lag (SAR) model is specified as

$$\ln P = \rho \boldsymbol{W} \ln P + \boldsymbol{X\beta} + \varepsilon,$$

whereas the spatial error model (SEM) is

$$\ln P = \boldsymbol{X\beta} + \varepsilon,$$

$$\boldsymbol{\varepsilon} = \lambda \boldsymbol{W} \varepsilon + u.$$

Measures of Spatial Effects

In the presence of spatial dependence, the interpretation of parameter β_j is different from a conventional least squares interpretation (LeSage and Pace, 2009). The OLS hedonic coefficient of an independent variable is interpreted as the *ceteris paribus* effect of the variable on a property's own value, which has no influence on the value of any other property under the *i.i.d.* assumption. In a spatial hedonic model, due to the spatial dependence among observations, any change in the characteristics of a property can affect the value of its neighbors, neighbors' neighbors, and so on. As the impact passes through neighbors, the value of that property will further be affected by the resulted value changes of its neighbors. Therefore, the impact of a change in variable X_j on the property is not simply the coefficient β_j, but the sum of all the subsequent effects on its own value that have taken place in the feedback loop. The magnitude of that impact depends on a number of factors, including the neighboring structure and connectivity among properties governed by the weight matrix $\boldsymbol{W}$, the spatial dependence measured by parameter ρ, and the coefficient estimate β_j.

Proposed by LeSage and Pace (2009), the partial effect of a change in an independent variable estimated from a spatial model can be summarized to an "average direct impact" and an "average total impact." In the context of the housing market, the average direct impact of an attribute measures the effect on the value of property *i* due to a change in the attribute of its own, taking all the spatial and feedback effects into account, while the average total impact measures the effect on the value of property *i* if all properties experience a change in that attribute, including the spatial and feedback effects. The difference between the "average total impact" and the "average direct impact" is the "average indirect impact," also known as the spillover effect.[8]

Empirical Specification and Identification

The environmental attribute of particular interest here is the water level in White Bear Lake. There are a number of reasons to believe that home buyers factor this into their willingness to pay for properties. First, lakeshore homeowners are among those who were strongly affected by the declining water level. Second, there has been extensive media coverage on the shrinking lake phenomenon, especially with the exposure of the USGS study and the lawsuit, so that potential home buyers are well aware of this issue. For example, a Google search for "White Bear Lake water level" returns numerous headlines from local newspapers, podcasts, and news stations. In addition, the White Bear Lake Restoration Association collects news and reports from various media sources related to White Bear Lake water issues and posts them in a designated section of its official website so that viewers can easily keep track of all the updates. More importantly, the public has learned from the USGS study and the lawsuit against the Minnesota Department of Natural Resources that the declining water level is not a natural fluctuation of lake water; therefore, home buyers are less likely to consider it a temporary shock.

[8] The SARAR model formulated in equations (3) and (4) can be expressed as

$$\ln \boldsymbol{P} = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{X\beta} + (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1} \boldsymbol{u}.$$

The matrix of partial derivatives of $\ln P_i$ with respect to X_j is defined as

$$\boldsymbol{S}_j(W) = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \beta_j,$$

then the scalar that measures *average direct impact* is

$$\frac{1}{n} tr(S_j(W))$$

and the scalar that measures *average total impact* is

$$(1-\rho)^{-1} \beta_j.$$

However, there is a concern that the estimated water-level effects from a hedonic model may be confounded by changes in the housing market over time. To identify the effect of water level on property value net of unknown market influences, it is necessary to find counterfactual properties with a lake environment and housing market similar to those in White Bear Lake but not affected by lake-level fluctuations. Nearby Bald Eagle Lake offers a solution to this problem. This lake is very close to White Bear Lake, with the shortest distance between the two shorelines less than 1.5 miles. The lakeshore properties along both lakes are all located in cities within Ramsey County or Washington County, so it is reasonable to consider them in the same local housing market. Bald Eagle Lake has been popular for boat fishing and other recreational use, and the benefits it provides to surrounding communities are similar to those provided by White Bear Lake. Most importantly, Bald Eagle Lake has not been affected by the groundwater overuse in Prairie du Chien–Jordan aquifer, and its water level has been relatively stable over the study period (Jones et al., 2013). Therefore, the lakeshore properties at Bald Eagle Lake are ideal counterfactuals for those near White Bear Lake. The properties located within 1 mile of White Bear Lake are defined as "treated" ($D_i = 1$), and those located within 1 mile of Bald Eagle Lake are considered as "control" properties ($D_i = 0$). Due to the close distance from the southeast shoreline of Bald Eagle Lake to the northwest shoreline of White Bear Lake, some properties fall into both the treatment group and the control group. To ensure clean identification, these properties are excluded from analysis.

Formally, the empirical specification based on the SARAR model is given by

$$\begin{aligned}\ln P = \rho \boldsymbol{W} \ln P + \boldsymbol{Z\gamma} + \alpha_1 (WL - OHWL)^2 \times D + \alpha_2 (WL - OHWL) \times D \\ + \alpha_3 DistWBL \times D + \alpha_4 DistBEL \times (1 - D) + \varepsilon,\end{aligned} \tag{5}$$

$$\varepsilon = \lambda \boldsymbol{W} \varepsilon + u. \tag{6}$$

P is the real sale value of a property in December 2014 dollars. WL is the water level in White Bear Lake at the month of sale. The value of lakeshore properties is vulnerable to water loss in the lake, whereas a high lake level may impose the risk of flooding. Moreover, the impact of water level on property value is likely nonlinear, in that the further the lake level deviates from the perceived normal level, the greater the impact. Therefore, the deviation of water level from the ordinary high water level, $(WL - OHWL)$, is used as the environmental variable of primary interest, and its quadratic term, $(WL - OHWL)^2$ is also included to capture the nonlinear effect.

The two water-level variables are interacted with the treatment variable, D, and the coefficients of the interaction terms are the treatment effects of changes in water level on property values without the interference of changes in housing market. $DistWBL$ and $DistBEL$ measure a property's distance to White Bear Lake and Bald Eagle Lake, respectively. Both distance variables are also interacted with the treatment (or control) indicator to separate out the effect of proximity to a lake from that of changing water level. $\boldsymbol{Z}$ is a vector of other independent variables that include

- housing structural variables: living area, the presence of garage, basement, and central cooling, age of the house, lot size;
- neighborhood and locational variables: school district, city, distance to the nearest highway, being close to Century College;
- other indicator variables: year and month of the sale.

Since the housing transactions in the data span from 1995 to 2015, it is likely that the hedonic equilibrium may have shifted over the study period, especially during the Great Recession in 2008. Therefore, "transaction year" fixed effects are included to allow the hedonic price function to shift over time as well as to control for impacts of business cycles. The lake elevation typically experiences seasonal changes, which may coincide with the seasonality of housing market; hence, "transaction month" indicators are included to control for the potential seasonal effects.

The weight matrix $\boldsymbol{W}$ is built based on the exact location of each property using their Universal Transverse Mercator (UTM) coordinates. A threshold distance of 740 meters is chosen to define neighborhoods in the spatial weight matrix because this is the minimum distance that ensures each property has at least one neighbor; otherwise, islands (properties with no neighbors) would be created. A binary weight matrix and an inverse distance weight matrix will each be used to test the sensitivity of the results to weight structure. As previously defined, spatial parameters ρ and λ measure the dependency between neighboring properties and the spatial correlation in errors, respectively, and $\boldsymbol{u}$ is an *i.i.d.* error term.

Results and Discussion

Estimation Results

The spatial hedonic model formulated in equations (5) and (6) is estimated by maximum likelihood.[9] A detailed discussion of the maximum likelihood estimator and its asymptotic properties can be found in Lee (2004). Table 3 reports the estimation results of main coefficients using two different types of matrices as well as those from a basic OLS hedonic model for comparison.

With either binary or inverse distance weights, the spatial dependence parameter, ρ, and the spatial error autoregressive parameter, λ, are both positive and highly significant, suggesting substantial spatial spillover effects in property value in the White Bear Lake housing market. Among the three specifications, the one using an inverse distance weight matrix provides the best fit based on the significantly higher R^2 and lower Aikake information criterion (AIC) and Bayesian information criterion (BIC). One noticeable difference is that the estimates of both ρ and λ from the inverse distance matrix are larger than those from the binary weight matrix. A possible explanation is that by setting different weights to neighbors based on distances, the inverse distance weight matrix better addresses the spatial heterogeneity in property value than the binary weight matrix. Compared to the OLS regression results, the general fit is greatly improved after controlling for spatial effects with either weight matrix. Since the specification using the inverse distance weight matrix outperforms others, the results (column 3, Table 3) will be the basis for remaining discussions.

Structural variables—such as "living area," "garage," "basement," "age," and "lot size"—are significant with expected signs. The negative and significant coefficient of "cooling" may at first appear counterintuitive. However, considering the cool climate in the study area and the additional maintenance costs involved, it is not surprising to see a cooling system negatively affect property value.[10] When using the OLS hedonic and the binary weights spatial specification, properties located in the Mahtomedi ISD are valued slightly higher than those in the White Bear Lake ISD at the 10% level of significance. However, in the spatial model with inverse distance matrix, the school district variable is no longer significant, suggesting that the school district effect captured by OLS is likely spurious due to spatial autocorrelation. After controlling for spatial effects, city indicators show that properties in the cities of White Bear Lake, White Bear Township, and Willernie are valued significantly lower than others. Year fixed effects are highly significant in most years. The signs and magnitudes of these estimates indicate that property values in the study area experienced steady growth through 2006, dropped drastically between 2007 and 2011, and then slowly recovered. This pattern coincides with the business cycle during the study period and can be reasonably explained by the fluctuations in the general housing market (e.g., the Great Recession in 2008). Month indicators capture significant seasonality in housing transactions: All else equal, properties are sold for relatively higher values in the summer (May to July) than at other times of the year.[11]

The treatment effects of environmental attributes on lakeshore properties are shown by the coefficients on interactions between the treatment variable, D, and the attributes. After controlling

[9] The estimation is executed by the "spmlreg" module in Stata (Jeanty, 2010).

[10] According to the daily weather records of the National Oceanic and Atmospheric Administration's National Centers for Environmental Information, July is the warmest month of the year in the White Bear Lake area, but the average temperature is only 72.3°F.

[11] City, year, and month fixed effects are not reported in the table but are available upon request.

Table 3. Estimation Results across Specifications (N = 4,611)

	Ordinary Least Squares (OLS) Hedonic	Spatial Hedonic (binary)	Spatial Hedonic (inverse distance)
Living area	0.0004***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Garage	0.1509***	0.1414***	0.1342***
	(0.0206)	(0.0196)	(0.0188)
Basement	0.1769***	0.1281***	0.1264***
	(0.0322)	(0.0311)	(0.0304)
Cooling	−0.1776***	−0.1736***	−0.1628***
	(0.0207)	(0.0198)	(0.0191)
Age	−0.0050***	−0.0052***	−0.0046***
	(0.0006)	(0.0006)	(0.0006)
Lot size	0.1778***	0.1614***	0.1551***
	(0.0219)	(0.0216)	(0.0214)
Distance to highway	−0.0000	−0.0000**	−0.0000*
	(0.0000)	(0.0000)	(0.0000)
College	0.0696***	−0.0624**	−0.0691**
	(0.0151)	(0.0254)	(0.0282)
Mahtomedi ISD	0.0731*	0.0807*	0.0423
	(0.0436)	(0.0441)	(0.0497)
$DistWBL \times D$	−0.0001***	−0.0001***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)
$DistBEL \times (1 - D)$	−0.0001***	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)
$(WL - OHWL)^2 \times D$	−0.0059**	−0.0048**	−0.0043**
	(0.0023)	(0.0022)	(0.0021)
$(WL - OHWL) \times D$	−0.0303**	−0.0286**	−0.0267**
	(0.0122)	(0.0121)	(0.0116)
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Constant	11.6284***	7.1598***	4.9286***
	(0.0598)	(0.5570)	(0.4977)
ρ		0.3745***	0.5564***
		(0.0440)	(0.0394)
λ		0.6721***	0.7328***
		(0.0654)	(0.0451)
R^2	0.698	0.702	0.814
Aikake information criterion (AIC)	1,632.482	1,270.788	925.311
Bayesian information criterion (BIC)	1,986.473	1,644.087	1,298.610

Notes: Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

for spatial effects and other influences from the housing market, the lake level still has significant impacts on properties surrounding White Bear Lake. The negative and significant coefficients on $(WL - OHWL)^2 \times D$ and $(WL - OHWL) \times D$ suggest an inverted U-shaped relationship between water level and property value. Intuitively, this means that, on average and all else equal, White Bear Lake properties are valued the highest when the lake is slightly below the ordinary high water level.[12] If the lake water drops below that benchmark, property values will fall at an increasing rate as the lake loses more water. On the other hand, if the water level is above that benchmark, as the water level rises further, property value will fall at an increasing rate as well. Overall, these estimates suggest that the impact of water level in White Bear Lake is significant and that home buyers factor the lake condition into their willingness to pay for lakeshore properties.

As suggested in the literature, proximity to water is an important attribute that affects property value. The negative and significant coefficients on the distance to White Bear Lake interacted with the treatment indicator D and the distance to Bald Eagle Lake interacted with the control indicator $1 - D$ imply that values of properties in both samples fall as distances from the lakes increase, *ceteris paribus*. These findings are consistent with previous studies, and show that consumers greatly value easy access to the lakes and the environmental benefits they provide (Brown and Pollakowski, 1977; Lansford and Jones, 1995a,b; Mahan, Polasky, and Adams, 2000; Loomis and Feldman, 2003).

Quantifying Loss

As discussed in the methodology section, in a spatial hedonic model the marginal effect of an attribute can be summarized by an "average direct impact" and an "average total impact." These measures can be used to quantify the monetary loss of property values in the White Bear Lake area as a result of the water-level decline. The average total impact is a more reasonable measure in this case because any change in lake water will affect all lakeshore properties. The average direct impact may not be as intuitive by itself, but it is a necessary component to compute the spillover effect. The spatial regression results reveal that after controlling for spatial effects and other influences from the housing market, there is an inverted U-shaped relationship between water level and property value. The exact impact of water level depends on how far off the water level is relative to the ordinary high water level. Following the measures of average direct and total effects defined in LeSage and Pace (2009) (see footnote 8) and accounting for this quadratic relationship, the average total impact of water level on properties in the White Bear Lake sample ($D_i = 1$) is derived from equations (5) and (6):

$$(1 - \rho)^{-1}[2\alpha_1(WL - OHWL) + \alpha_2]. \tag{7}$$

We can see from this measure that the impact of water level on property value not only depends on the coefficient estimates on the water-level variables α_1 and α_2 but also factors in the spatial dependence parameter, ρ, and the actual elevation of lake water.

To illustrate how property values are affected by the loss of water in White Bear Lake, the lowest recorded lake elevation is used for a scenario analysis. In January 2013, White Bear Lake hit a record low water level of 918.84 feet, which was approximately 6 feet below the ordinary high water level. Substituting this deviation of 6 feet along with the estimates from the spatial regression with inverse distance matrix into expression (7) yields the average total impact. The average direct and indirect impacts can also be calculated using the same parameter estimates. For comparison, the estimated effects from the binary weights specification and the OLS hedonic model are also calculated. Table 4 summarizes these effects along with the bootstrapped 95% confidence intervals for the estimates of average total impacts. All three specifications predict statistically significant and tremendous loss in property value as a result of water loss in the lake. The spatial hedonic model using inverse distance

[12] Based on the coefficient estimates from the spatial hedonic model with an inverse distance weight matrix, this bench mark is calculated to be 3.10 feet below the ordinary water level.

Table 4. Impacts of Water Loss on Property Value across Specifications

	Ordinary Least Squares (OLS) Hedonic (%)	Spatial Hedonic (binary) (%)	Spatial Hedonic (inverse distance) (%)
Average direct impact	–	8.613	7.907
Average indirect impact	–	5.141	9.804
Average total impact	10.056	13.754	17.711
95% confidence interval	(2.383, 17.728)	(3.995, 23.513)	(10.573, 24.849)

Notes: These estimates measure the loss of property value if the water level hypothetically declines 1 more foot from the level of 918.84 feet in January 2013. The confidence intervals for the estimates of average total impacts are calculated using bootstrapped standard errors.

weights seems to provide a larger loss estimate than the other two specifications; however, due to the overlaps between the confidence intervals, the evidence of size differences is relatively weak.

The interpretation of these measures is straightforward. When the lake water is as low as 6 feet below the ordinary high water level, an additional foot of water-level decline will lead to a 17.711% loss of property value, *ceteris paribus*. The spillover effects that arise from the spatial influences among properties account for 9.804% of the total loss. Evaluated at the mean real sale value of the White Bear Lake sample (i.e., $296,274.10), the marginal implicit loss associated with an additional foot of water-level drop, when the water level is 6 feet below the ordinary high water level, is $52,473.11 for an average property.

Overuse of an underground aquifer is the primary cause of water loss in White Bear Lake. The shrinking lake, however, is hardly a sign of water shortage, considering Minnesota is a water-rich state endowed with approximately 10,000 lakes. The issue instead lies in the management and allocation of water. According to the Minnesota Water Use Data (Minnesota Department of Natural Resources), over 75% of the state's water supply is from groundwater. Groundwater pumping is growing faster than the state's population, and groundwater usage is already unsustainable in some parts of the state (Freshwater Society, 2013). The fundamental root of this problem is the seemingly "rational" logic: Groundwater is abundant and requires little to no treatment; thus, extracting groundwater for municipal use is much "cheaper" than using surface water. The loss in property value surrounding White Bear Lake is simply an externality of groundwater overuse. If this externality is accounted for, groundwater is not cheap after all.

Conclusions and Policy Implications

Using detailed MetroGIS parcel data in the White Bear Lake area and a spatial hedonic method, this paper identifies and estimates the loss in property value as a result of the persistently declining water level in White Bear Lake. The study has two major contributions to the literature of environmental resource evaluation. First, it incorporates spatial econometric techniques into a hedonic framework, which allows for spatial dependence in property value arising from both the spatially lagged dependent variable and the errors. Such spatial dependence commonly exists in real estate markets; ignoring this dependence could result in biased estimates and inaccurate forecasts. Second, literature in water resource evaluation primarily focuses on other attributes of water bodies, such as water quality and view, but little attention has been paid to water-level fluctuations. This paper assesses the value of maintaining sufficiently high water level in a public lake, which fills in a gap in the current literature.

The results of this study provide significant evidence for the presence of spatial dependence in the real estate market surrounding White Bear Lake. Spatial diagnostic tests indicate strong spatial correlation in both the dependent variable and the error. The comparison with an alternative OLS hedonic specification shows the bias resulting from ignoring the spatial dependence in property values. Overall, the empirical findings support including spatial components in hedonic housing price models in order to obtain unbiased and efficient estimates.

Consistent across all three specifications, water-level decline in White Bear Lake has had a significantly negative impact on lakeshore properties. The relationship between property values and the water level can be depicted by an inverted U shape, and lakeshore properties are valued highest when the lake is 3.10 feet below the ordinary high water level. This parabolic pattern suggests that homeowners value sufficiently a high and stable water level in the lake; deviations from that benchmark will likely reduce their willingness to pay for lakeshore properties.

This study provides a quantitative estimate of the impact of water loss on property value that takes into account spatial spillover effects. When the lake elevation drops to 6 feet below the ordinary high water level, the marginal implicit price of an additional foot of water loss is estimated to be $52,473.11 for an average property in the White Bear Lake sample.

Finally, the findings of this study shed light on water resource management in emerging urban areas. Population growth, urbanization, and economic development all impose increasing demand for water use. A big challenge facing policy makers is how to meet demand while maintaining a sustainable balance between groundwater pumping and surface water allocation. The shrinking White Bear Lake is just one example of this conflict. The results of this study indicate that consumers value a sufficiently high water level in the lake and the sustainable management of groundwater. This demand should be given adequate consideration when making decisions on allocating scarce water resources.

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