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The impact of water quality in Narragansett Bay on housing prices

Tingting Liu
University of Nebraska-Lincoln, tliu19@unl.edu

James J. Opaluch
University of Rhode Island

Emi Uchida
University of Rhode Island

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Tingting Liu
University of Nebraska at Lincoln

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Key Points:
- Examine the impact of water quality on housing prices spatially
- Test perceptions of water quality using different measures
- Find that people are more concerned with extreme events and the impact of water quality on housing prices varies by distance

Supporting Information:
- Supporting Information S1

Correspondence to:
T. Liu,
gnuliutingting@gmail.com

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The impact of water quality in Narragansett Bay on housing prices

Tingting Liu[1], James J. Opaluch[2], and Emi Uchida[2]

[1]ORISE Participant with U.S. EPA, Cincinnati, Ohio, USA, [2]Department of Environmental and Natural Resource Economics, University of Rhode Island, Kingston, Rhode Island, USA

Abstract We examine the impact of water quality in Narragansett Bay on housing prices in coastal towns and cities using a hedonic housing-price model. Unlike other hedonic studies of water quality, we test whether housing market responds to average water quality or more to extreme events. We also test the spatial and temporal extent of effects of water quality on housing prices. We find that poor coastal water quality, measured in terms of the concentration of chlorophyll, has a negative impact on housing prices that diminishes with distance from the shoreline. Furthermore, our finding suggests that housing prices are most influenced by the extreme environmental conditions, which may be accompanied by unpleasant odors, discoloration, and even fish kills. We further predict potential increases in home values associated under water quality improvement scenarios and find an increase in the values of homes in coastal communities along Narragansett Bay of about $18 million up to $136 million.

1. Introduction

Marine and coastal environments provide a wide range of ecosystem services to society, including aesthetic value, provision of farmed and wild seafood for consumption, recreational opportunities, nutrient cycling and filtering of waste, coastal and natural hazard protection, and carbon storage for climate regulation [*Chan and Ruckelshaus*, 2010]. However, many estuarine and coastal ecosystems are used intensively, leading to damage to natural systems [*Barbier*, 2012]. Evidence is accumulating that changes in land uses and climate are two important drivers of such damage [*Schröter et al*., 2005]. For example, excess nutrients from residential and agricultural activities can enter estuaries, causing eutrophication of the waterbody that leads to severe reductions in dissolved oxygen, declines in eelgrass and submerged aquatic vegetation, fish kills, and algal blooms in coastal estuaries [*Anderson et al*., 2002; *Lotze et al*., 2006]. Despite the importance of coastal and marine ecosystems and the services they provide and the significant threats to their survival, few studies have evaluated the welfare impacts of changes in coastal ecosystem services.

This study measures the effect of coastal water quality on housing prices using the hedonic price method. The hedonic approach has been widely used to examine the relationship between housing prices and environmental amenities [*Paterson and Boyle*, 2002], including air quality [*Harrison and Rubinfeld*, 1978; *Smith and Huang*, 1995], open space [*Anderson and West*, 2006; *Bolitzer and Netusil*, 2000; *Sander and Polasky*, 2009], wetlands [*Mahan et al*., 2000; *Paterson and Boyle*, 2002], and disamenities such as landfills and odors from farms [*Boyle and Kiel*, 2001; *Ready and Abdalla*, 2005]. Most of the earlier work on water quality focused on freshwater lakes [*Boyle and Taylor*, 2001; *Gibbs et al*., 2002; *Poor et al*., 2001; *Walsh and Milon*, 2016] and found that better water quality was associated with higher property values. *Dornbusch and Barrager* [1973] and *Anderson and West* [2006], for example, found positive amenity values associated with proximity to a waterbody that extended as much as several hundred meters from the shore. *Walsh et al*. [2011] examined the effects of enhanced water quality on prices for waterfront and nonwaterfront properties and found that the value of increased water quality depended on the property's location and proximity to the waterfront and that the impact extended up to 1000 m from the lake.

We make several important contributions to the literature. Generally, this study provides new empirical evidence of how water quality affects welfare. Some empirical studies assess the impacts of estuary water quality on coastal housing prices. *Leggett and Bockstael* [2000] found that water quality had a significant effect on the value of properties along Chesapeake Bay. They addressed omitted-variable bias by including several variables as proxies for the direct effect of the source of the pollution. *Bin and Czajkowski* [2013] compared the impacts of technical and nontechnical measures of water quality on coastal waterfront property values in Martin County in Florida and found that the technical measure provides better predictions of housing prices than the nontechnical "location grade" index. We provide additional evidence on appropriate metrics of water quality in the context of a case study of Narragansett Bay, USA, where there have been significant changes in water quality over the past two decades.

Specifically, we examine alternative water quality indicators and identify whether the housing market responds to typical conditions versus more extreme water quality. A critical problem that has generally been overlooked is that market prices could respond differently to average water quality and the poorest water quality [*Gibbs et al*., 2002]. Earlier studies mostly used mean or median values for water quality in the year in which a home was sold [*Bin and Czajkowski*, 2013; *Leggett and Bockstael*, 2000; *Poor et al*., 2001; *Walsh et al*., 2011]. However, typical or average conditions could be most influential in determining housing prices, or extreme conditions like discoloration and unpleasant odors could be most influential. Since information on home buyers' perception is unavailable, we use the water quality metrics as proxies to identify which model appears to best represent the effects of water quality on the market equilibrium. Our study contributes to the literature by examining whether housing prices are influenced primarily by typical conditions, or by rare but extreme adverse environmental events. This improved information on the most influential water quality conditions allow us to better estimate the potential benefits of improved water quality for home sale prices.

Another important issue associated with the impact of water quality on housing prices is the amount of information homebuyers need about the quality of the water when making purchase decisions. The only study of that issue to date is *Michael et al.* [2000], which used a survey of buyers of lake properties in Maine and found that buyers obtained several types of information about the lakes' water clarity. The researchers used the water's current and historical clarity and/or the change in clarity during summer months to reflect buyers' potential perceptions and found that their perceptions about the water's clarity had a substantial impact on implicit prices.

Additionally, we contribute to the literature by examining the spatial and temporal extent of the effect of water quality on housing prices. Specifically, we test two models to examine the effect of the amount of information obtained by buyers. The "well-informed" model assumes that buyers observed the quality of the water over an extended period of time and the "myopic" model assumes that buyers relied only on the most recent water quality conditions. The "myopic" model is associated with a water quality impact on housing prices that decays rapidly over time. In contrast, the "well-informed" model is associated with a water quality impact on prices that is more persistent over time.

Furthermore, we examine the impact of water quality on housing prices spatially by testing various distances between homes and the waterbody and determine whether there is a threshold distance beyond which the quality of the water does not affect home prices. To our knowledge, the two prior studies to have used distance buffers to examine the impacts of water quality are *Netusil et al*. [2014] and *Wolf and Klaiber* [2017]. *Netusil et al*. [2014] incorporated buffers of one-quarter mile (402 m), one-half mile (805 m), 1 mi (1609 m), and more than 1 mi from a creek to estimate the impacts of changes in dissolved oxygen on housing prices. *Wolf and Klaiber* [2017] used both discrete and continuous variables for lake proximity measures, such as properties located next to the lake and near the lake by using the properties located on the shoreline, 300 m, and 600 m distance "donut" bands. They also allowed the proximity effect to vary continuously within each distance bands. Identification of such thresholds is particularly useful when measuring, describing, quantifying, and mapping the value of ecosystem services [*Polasky et al*., 2015]. Finally, spatial correlation between water quality and housing transactions could bias the estimates generated by the model so must be taken in account. We estimate the hedonic housing-price models with ordinary least squares (OLS) and then test and correct for spatial autocorrelation.

2. Background

Narragansett Bay forms the largest estuary in New England and has an area of about 150 mi^2 (385 km^2) of surface water [*Watershed Counts*, 2014]. The bay's watershed is more than 10 times larger, covering a land area of 1675 mi^2. Approximately, 40% of the watershed is in Rhode Island and the other 60% is in Massachusetts (see Figure 1). Since more than 100 towns and cities are located in the watershed, it is difficult to

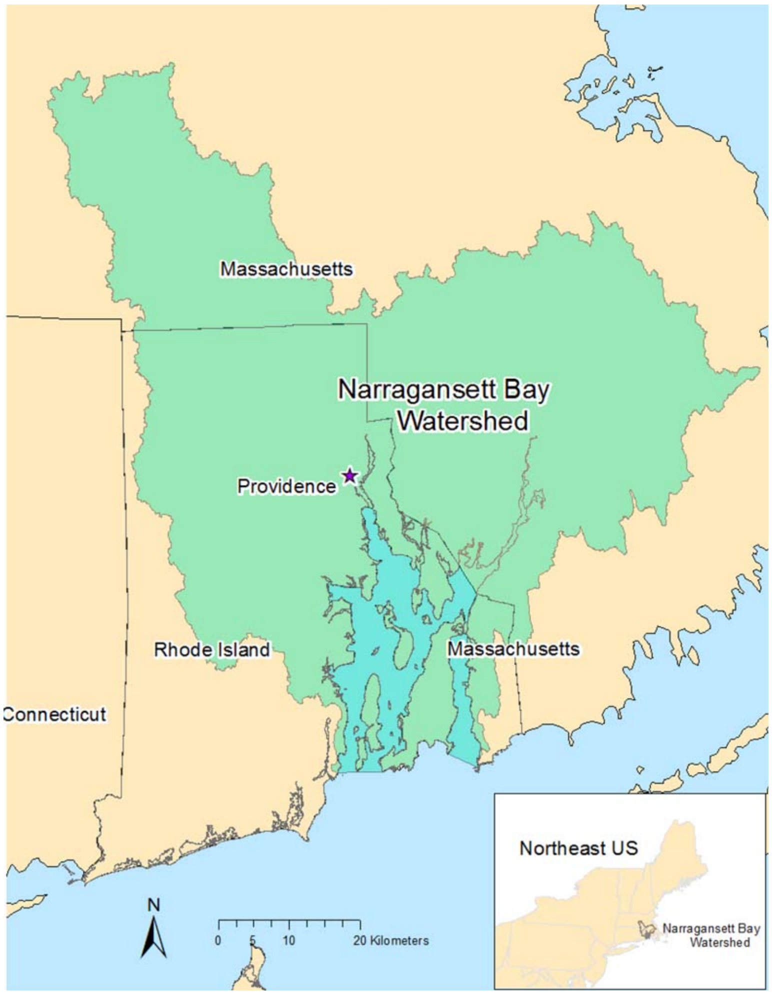

Figure 1. Location of the Narragansett Bay Watershed.

control pollutants entering Narragansett Bay and improve the bay's water quality. Historically, the pollutants have been mostly nutrients coming from inland runoff and wastewater treatment facilities (WWTFs) [*Rhode Island Department of Environmental Management*, 2000]. A 28% population increase in the watershed—from 3.8 million in 1960 to 4.9 million in 2000 has led to major construction, increasing the burden on WWTFs [*Narragansett Bay Commission*, 2012]. In addition, the amount of land devoted to urban uses increased by 44% (from 17,280 to 24,901 ha) between 1972 and 2010 [*Archetto and Wang*, 2012] with significant conversions in the watershed adjacent to coastal communities. The nutrient loads have exacerbated deterioration of water quality in Narragansett Bay, and eutrophic conditions, including a lack of dissolved oxygen, fish kills, destruction of eelgrass, and algal blooms, are appearing more frequently [*Rhode Island Department of Environmental Management* (*RIDEM*), 2003]. *RIDEM* [2003] reported that in 2003 more than 1 million fish died from anoxia, a total depletion of oxygen, an event that called attention to the poor health of Narragansett Bay.

Since 2003, various regulatory and nonregulatory programs have been implemented to improve water quality in the bay by establishing water quality standards, monitoring the water quality, restoring habitat, and developing and implementing watershed action plans [*RIDEM*, 2003]. Several programs have specifically targeted point and nonpoint sources of pollution, including upgrades to municipal WWTFs and development of a combined sewage overflow program [*U.S. Environmental Protection Agency (US EPA)*, 2008]. In addition, Rhode Island passed a law in 2004 to reduce nitrogen loads from major WWTFs by 50% of the 1995/96 levels by 2008 [*US EPA*, 2008]. Other measures include implementation of storm water regulations and adoption of low-impact development approaches throughout the watershed to protect rivers and lakes and thus contribute to improved water quality in the bay [*Watershed Counts*, 2014]. Water quality has improved in some parts of the bay with dissolved oxygen approaching unimpaired levels [*Watershed Counts*, 2014].

The economic benefits from improved water quality in Narragansett Bay have not been assessed. The only study of the potential benefits [*Hayes et al*., 1992] was done more than two decades ago. This study used a contingent valuation method to estimate the willingness to pay to obtain fishable and swimmable water quality conditions and found aggregate annual benefits in the range of $30 million to $60 million to obtain swimmable quality and $30 million to $70 million to obtain shell-fishable quality. This study used mean and median measures of water quality.

To examine the impact of improvement in water quality on the housing market as measured by price premiums for home sales, we focus on coastal municipalities in Rhode Island that have coastal access: Barrington, Bristol, Cranston, East Providence, North Kingstown, Pawtucket, Providence, Warwick, East Greenwich, and Warren. We omit coastal communities in Massachusetts and a portion of Rhode Island because most of the water monitoring stations are on the west side of Narragansett Bay.

3. Hedonic Model Estimation

The theoretical framework of our hedonic price model is built on the basic utility maximization problem of consumers [*Taylor*, 2003]. When consumers choose between differentiated goods or services, the price at the equilibrium will reflect implicit prices for particular characteristics of each good or service [*Rosen*, 1974]. Residential properties can be characterized as three bundles of characteristics: the property, the surrounding neighborhood, and the local environment. Each property offers a particular bundle of characteristics, and buyers can maximize utility through their selection of a property. From a supply perspective, sellers maximize their profits. At the equilibrium, the hedonic housing-price function can be expressed as

$$Price = F(\mathbf{H}, \mathbf{N}, \mathbf{E}) \tag{1}$$

where *Price* is the amount for which the property was sold and **H** is a vector of housing-related characteristics such as lot size, living area, the number of bathrooms, and the condition of the property. **N** is a vector that represents neighborhood characteristics such as the quality of the local school district, the crime rate, and public services provided in the neighborhood. **E** is a vector that represents environmental amenities and disamenities.

The effect of water quality on housing prices can be used to improve our understanding of buyers' perceptions of water quality. *Michael et al*. [2000] found that information on historical and current water quality is a critical factor in homebuyers' purchase decisions. To address this issue, we employ two simplified models: the well-informed model in which homebuyers reach their decisions using information on both historical and recent water quality and the myopic model in which purchase decisions are based only on recent information on water quality. The well-informed model and the myopic model can be written as

$$\ln\left(Price_{it}\right) = \beta_0 + \beta_1 \boldsymbol{WQ}_{\boldsymbol{i(t)}} + \boldsymbol{\beta}_2 \mathbf{Distance}_i \times \boldsymbol{WQ}_{\boldsymbol{i(t)}} + \boldsymbol{\beta}_3 \mathbf{Distance}_i + \boldsymbol{\beta}_4 \times \boldsymbol{H}_i + \boldsymbol{\beta}_5 \times \boldsymbol{N}_i + \boldsymbol{\alpha}_{town} + \gamma_{year} + \varepsilon_{it} \tag{2}$$

We adopt the semilog functional form because our Box-Cox test results show that semilog form (log form for the transaction prices and linear form for the water quality indicator) is the most appropriate model for our case study. Additionally, the semilog specification has been frequently used in hedonic studies [*Palmquist*, 1984; *Kim et al*., 2003; *Poor et al*., 2007]. $Price_{it}$ is the transaction price for property *i* at time *t*, and $\boldsymbol{WQ_i}$ and $\boldsymbol{WQ_{it}}$ represent a vector of corresponding water quality indicators for the well-informed model and the myopic model, respectively. The only difference between the two models is the amount of water quality information used for purchase decisions.

$\mathbf{Distance}_i$ represents a vector of dummy variables that measure the proximity of property *i* to the shoreline divided into categories: 100 m or less; 100–750 m; 750–1500 m. Greater than 1500 m is our baseline, and we assume that coastal water quality has little impact on the housing price beyond this threshold. In order to determine the specific distance where the effect drops off, we use 22 dummy distance dummy variables at 100 m intervals (0–100, 100–200, 200–300 m, . . ., 2000–2100, and greater than 2100 m). Then, we run our model and our results suggest that the distance water quality interactions become insignificant above

1000 m and the distance impacts become insignificant above 1500 m. To be conservative, we chose 1500 m as the bench mark which is also consistent with the hedonic literature [*Netusil et al*., 2014; *Wolf and Klaiber*, 2017]. We use distinct distance categories because it has the advantage of capturing nonlinear effects unlike a continuous distance variable. We found the results are robust to different specifications for distance (supporting information Tables S4). As robustness checks, we also tried a continuous variable for distance, as well as other specifications for distance buffers (supporting information Tables S5 and S6).

We hypothesize that, all else equal, houses near shorelines with high quality water will sell for a premium relative to houses further from shore. But as water quality declines, the price premium for being near the shoreline declines and may be negative if water quality is very poor. This implies that proximity to the shoreline has a positive effect but the interaction of worse water quality and proximity is negative. We therefore expect the coefficients on the distance dummy variables to be positive and decreasing. We further expect the interactions between chlorophyll concentrations and distance to be negative and decreasing in absolute value so that water quality has the largest effect on the price of properties located very close to the shoreline and less of an effect on the price of properties farther from the shore.

Other control variables include standard housing-related characteristics, $\mathbf{H}_i$, such as the lot size, number of years since renovation, number of fireplaces, condition of the house on a scale of 1–11 in which 1 represents unsound and 11 represents excellent condition, living area, and the square term of the living area, the number of bathrooms, half baths, air conditioning (1= Yes), a pool (1= Yes), and a dock (1= Yes). We include the distance to the downtown area of the state capital and distance to the nearest highway exit, since proximity to the central market and commuting time may be important determinants for property values [*Samuelson*, 1983]. For neighborhood characteristics ($\mathbf{N}_i$), we control for characteristics of the census block in which the property is located, including the percent of residents older than 65, median household income, and population density of the tract using information obtained from the U.S. Census Bureau.

The town (α_{town}) and year (γ_{year}) fixed effects control for unobserved characteristics for different coastal towns and for different sales years. We use robust standard errors clustered at water quality regions that are based on Rhode Island's Integrated Water Quality Monitoring and Assessment Report 2010 to control for heteroskedasticity associated with potential measurement errors and systemic errors in the process of predicting or interpolating water quality.

Lastly, the model accounts for potential spatial correlation in housing prices and model errors [*Anselin*, 1988]. For example, the price of one house can affect prices for other houses in the neighborhood and vice versa. When there are unobserved variables that relate to the location of the house, the errors of the model can be spatially correlated and further bias the estimation results [*Pandit et al*., 2013]. We extend equations (2) and (3) to take both spatial lag and spatial errors into account. (We estimated spatial fixed models at census tract or block group level, which improved the goodness of fit. However, Moran's I statistics and Lagrange multiplier tests are still significant which indicates the existence of spatial autocorrelation.)

$$\ln(Price_{it}) = \rho_i \boldsymbol{W}_1 \ln(Price_{it}) + \beta_0 + \beta_1 \boldsymbol{WQ_{i(t)}} + \beta_2 \mathbf{Distance}_i \times \boldsymbol{WQ_{i(t)}} + \beta_3 \mathbf{Distance}_i + \boldsymbol{\beta}_4 \times \boldsymbol{H_i} + \boldsymbol{\beta}_5 \times \boldsymbol{N}_i + \boldsymbol{\alpha}_{town} + \boldsymbol{\gamma}_{year} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda_i \boldsymbol{W}_2 \varepsilon_{it} + u_{it} \tag{3}$$

where ρ_i is the spatial lag coefficient; λ_i is the spatial error coefficient; and u_{it} is the error term, which is assumed to be independently and identically distributed, and $u_{it} \sim N(0, \sigma^2)$. $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are row-standardized n $\times$ n spatial weight matrices that define the neighboring units and their influence [*Anselin*, 1988; *Pandit et al*., 2013].

We explored the presence of spatial lag and error dependence. The most common approaches to defining spatial weight matrices are nearest neighbor, cutoff distance, and nearest neighbor within a cutoff distance. We use the *k*-nearest-neighbor approach (four, six, and eight nearest neighbors) since it has been used frequently in other studies [*Mueller and Loomis*, 2008; *Netusil et al*., 2014; *Pandit et al*., 2013].

Commonly used spatial tests including Moran's I, the Lagrange Multiplier, and the Robust Lagrange Multiplier, and Akaike information criterion (AIC) statistics all confirm that the spatial error model is the more appropriate specification and that use of eight nearest neighbors gives the best hedonic estimation.

However, results are robust with respect to specification for the three nearest-neighbor specifications (four, six, and eight).

3.1. Housing Data

We started with 316,553 housing transactions in Rhode Island for 1992–2013. To adjust the home sale prices, we used the S&P/Case-Shiller Ma-Boston home price index because it measures the average change in the total value of repeat-sale single-family-home prices in the greater Boston metropolitan area and is recognized as the most reliable means of measuring movement in housing prices [*Shiller*, 2007]. We also compared our adjusted prices for Rhode Island homes to similarly adjusted prices for homes in Boston and the average home nationwide. We found that the fluctuations in home prices in Boston were smaller (they increased slowly and dropped slowly) relative to the national average before and after the 2007 housing market depression. Using the Boston quarterly home price index, we adjusted all of the Rhode Island housing transaction prices to 2013 first-quarter prices. To ensure that we analyzed only arm's length sales (the buyers and seller were independent and had no relationship), we dropped transactions of less than $40,000 after adjusting the prices. By selecting geocoded property sales that occurred in our study area of 10 coastal towns and cities in Rhode Island using ArcGIS, we obtained a data set consisting of 27,040 single-family residential properties and 40,433 housing transactions. Summary statistics of the property transactions are shown in Table 1.

To capture factors previously found to influence housing prices, we include variables for housing characteristics in the model: lot size in hectares, number of years since the house was renovated, number of fireplaces in the building, the condition of the building on a scale of 1–11 (1 = Unsound, 11 = Excellent), living area in hundred square meters, number of bathrooms, and number of half baths (a bathroom in a private home that contains a toilet and sink but no bathtub or shower), air conditioning (1= Yes), a pool (1= Yes), and a dock (1= Yes). Square terms of the lot size and of the living area are included to capture the nonlinear relationship between housing-related characteristics and prices. The condition of the building is an important factor in buyers' purchase decision making. However, most of hedonic literature has not considered the condition of the house. A neglected house could be decaying and broken down even if it was built relatively recently, while a properly maintained house could be excellent condition even if it were old. This could have a large effect on sales price, and conventional attributes such as lot size, size of living area, number of bathrooms, and age of the house do not provide us this information.

We also include distance to downtown Providence in kilometers, distance to the nearest highway exit in kilometers, and distance to the nearest shoreline as four categorical dummy variables—less than or equal to 100, 100–750, 750–1500 m, and greater than 1500 m—to capture the possible nonlinearities in the relationship between distances and housing prices. The number of property transactions in each distance buffer is shown in Table 2.

Table 1. Variables and Descriptive Statistics of Housing Transaction in Coastal Municipalities of Narragansett Bay (1992–2013)

Variable	Units	Mean	Std. Dev.	Min	Max
Adjusted housing price (in the first quarter of 2013 housing price index)	Thousand 2013 dollars	348.06	258.22	60.15	4626.80
Distance to downtown Providence	km	12.87	7.64	0.32	36.87
Distance to nearest highway exit	km	3.35	2.53	0.05	11.34
Distance to nearest shoreline	km	2.32	2.23	0.01	12.41
Lot size	ha	0.16	0.26	0.01	9.43
Number of years since renovation		57.80	32.04	2	334
Number of fireplaces in the building		0.44	0.62	0	6
Condition of the house (1–11, 1 = unsound, 11 = excellent)		5.41	0.89	1	11
Living area	100 m^2	1.67	0.76	0.40	10.22
Number of bathrooms		1.57	0.69	1	7
Number of half baths		0.48	0.54	0	3
People older than 65 in the neighborhood	%	0.15	0.07	0.00	0.57
Population density in the neighborhood	Thousand people per square kilometer	11.82	13.11	0.63	125.67
Median household income in the neighborhood	Thousand 2000 dollars	55.72	22.23	8.64	125.97

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Table 2. Distribution of Property Transactions in the Coastal Municipalities of Rhode Island for 1992–2013

Distance to Nearest Shoreline	Number of Property Transactions	Percent of Total Transactions	Cumulative Percent of Total Transactions
100 m or less	592	4.22	4.22
100–750 m	3519	25.10	29.32
750–1500 m	2451	17.48	46.80
Greater than 1500 m	7458	53.20	100

3.2. Indicator of Water Quality in Narragansett Bay

Three primary water quality concerns for Narragansett Bay are eutrophication, nutrient loading, and the presence of pathogens [*US EPA*, 2008]. Contamination with pathogens typically affects recreational activities, but nutrient loading and subsequent eutrophication can have far-reaching impacts on ecosystems. Excess nitrogen can induce algal blooms during warm months [*Conley et al*., 2009]. When algae use up all of the nutrients in the water, they die and sink to the bottom, where they are decomposed by bacteria. Bacteria consume oxygen in the process, depleting oxygen levels near the bottom, and the resulting eutrophication kills the plants and animals that inhabit the water. Eutrophication can also reduce the water's clarity and generate unpleasant odors, further reducing the value of nearby properties.

Various indicators of water quality have been used in hedonic studies, including levels of chemicals (total nitrogen, total phosphorus, and dissolved oxygen) and total suspended solids, temperature, pH, and concentrations of fecal bacteria [*Leggett and Bockstael*, 2000; *Netusil et al*., 2014; *Poor et al*., 2001]. The most commonly used indicators are water clarity [*Gibbs et al*., 2002; *Michael et al*., 2000; *Walsh and Milon*, 2016; *Walsh et al*., 2011] and level of pathogens [*Leggett and Bockstael*, 2000]. *Walsh et al*. [2011], *Netusil et al*. [2014], and *Walsh and Milon* [2016] used single indicators while *Bin and Czajkowski* [2013] and *Walsh and Milon* [2016] used multiindicator composites.

Our indicator of water quality is the concentration of chlorophyll (in micrograms per liter (μg/L) in the water. Chlorophyll accumulates in waterbodies in response to nutrient loads and its concentration is often one of the standards set in a total maximum daily load (TMDL) program by the US EPA [*Walsh and Milon*, 2016]. The chlorophyll concentration is easily measured by simply observing the degree of green color on the surface of coastal waters, while other water quality indicators, such as temperature, salinity, dissolved oxygen, and pH, require more expensive monitoring programs. The presence of pathogens is likely to influence prices for nearby homes, but no such data were available for most of the Narragansett Bay estuary. Since a joint *F* test shows that most water quality indicators are highly correlated, we restricted out analysis to the chlorophyll concentration. (results are available upon request.)

The water quality data for 1999–2013 used in the study came from fixed-site monitors and buoys in Narragansett Bay and were obtained from Rhode Island Department of Environmental Management (RIDEM) through a collaboration of a number of agencies that measure the bay's temperature, salinity, dissolved oxygen, pH, and chlorophyll level every fifteen minutes. The chlorophyll concentration data were collected at thirteen monitoring stations, and we aggregated the 15 min measurements into the daily average chlorophyll concentration for each monitoring station (see supporting information Table S1). We use water quality monitoring data during the summer (1 May through 30 September) because water conditions are prone to hypoxia and anoxia when the temperature is high [*Rhode Island Department of Environmental Management* (*RIDEM*), 2012].

One challenge in assessing the amenity value of coastal water quality is the accuracy of the water quality data. While water quality in a small lake can be assumed to be relatively homogeneous, the water quality in a large saltwater estuary can vary significantly spatially and typically is monitored at a small number of stations. Therefore, it is difficult to capture the estuary's hydrodynamics, bathymetry, and biochemistry using interpolation methods [*Murphy et al*., 2011]. To our knowledge, *Leggett and Bockstael* [2000] is the only study that has accounted for the accuracy of estuary water quality in the analysis. They used inverse distance-weighted (IDW) averages of readings from the three nearest monitoring stations to calculate counts of fecal coliform bacteria in Chesapeake Bay. Early in our research we learned from experts in physical oceanography of the Narragansett Bay that because of tidal flows, river inflows and other water currents, there are distinct water quality regions in the estuary. These oceanographic conditions imply that water

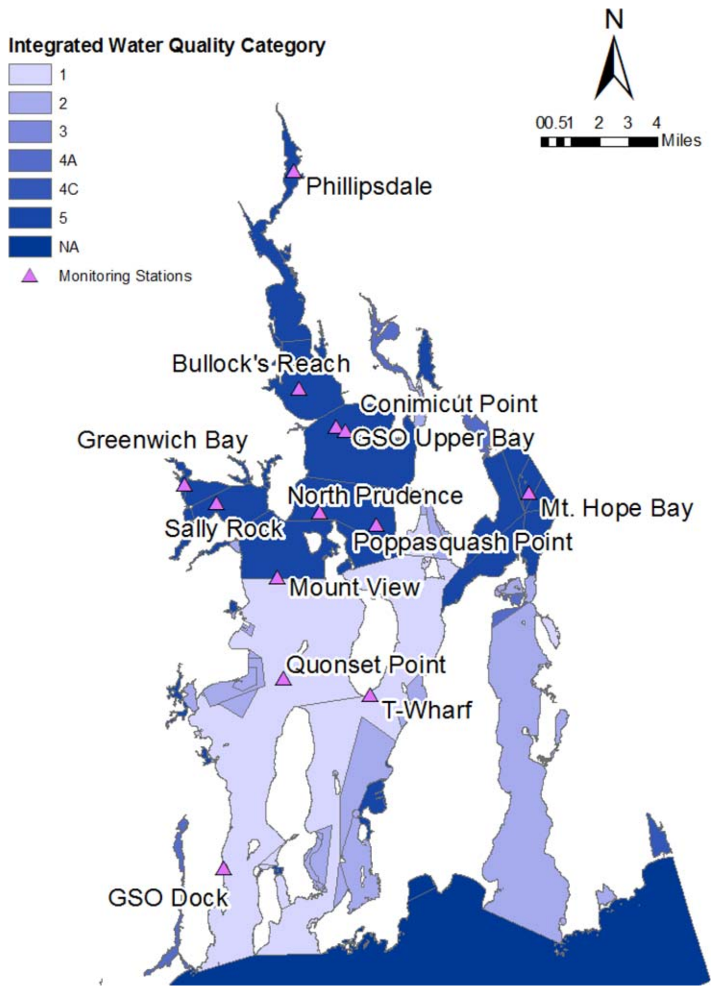

Figure 2. Assessments of water quality and the location of monitoring stations at Narragansett Bay (*Source*: Rhode Island Geographic Information System).

quality at a location within a region is accurately represented by using distance-weighted measures from monitoring stations within the region, and excluding water quality measure from monitoring stations that are physically close but are located within a different water quality region. For this reason, we modified the IDW approach by calculating distance-weighted averages only using data from monitoring stations within the water quality region relevant for each transaction. We believe this improves on the standard IDW approach, at least for estuaries like Narragansett Bay, which have well defined water quality regions.

In line with the federal Clean Water Act, Narragansett Bay has been segmented to reflect hydrologic drainage basins, differences in the degree of water quality, land use changes, and areas designated for shellfish aquaculture [*RIDEM*, 2012]. The water quality assessments are made using a scale of 1–5 (1 represents poor quality and 5 represents excellent quality) and are based on thorough evaluations of the segments' overall water quality for all designated uses, which can include public drinking water, recreational activities, fish and wildlife habitat, industrial cooling, and agriculture (Rhode Island Section 303(d) List of Impaired Waters) [*RIDEM*, 2012]. The assessments of water quality and location of the monitoring states are shown in Figure 2. This information facilitates interpolation and analysis of the data since water quality in the estuary is difficult to predict at a specific location without actual monitoring due to tidal movements, flow patterns, and other geographic conditions [*Murphy et al.*, 2011].

We use the water quality assessments and IDW method to interpolate water quality for each water subregion.

$$Chlorophyll_i = \frac{\sum_{j=1}^{n} 1/d_j Chlorophyll_j}{\sum_{j=1}^{n} 1/d_j} \quad (4)$$

$Chlorophyll_i$ is the chlorophyll concentration associated with property i, d_j is the distance from property i to the jth closest monitoring station in kilometers in the same water quality subregion, and $Chlorophyll_j$ is the chlorophyll concentration at the monitoring stations j. We use the Euclidean distance between the property (the transaction point) and the monitoring stations to interpolate water quality using ArcGIS software since it serves a good proxy of the road distance [*August*, personal communication, 2014]. When there is a single monitoring station within a water quality subregion, the water quality measured at that station is used for all of the properties in the subregion. When there is more than one monitoring station in a subregion, the spatial distribution of water quality is measured by interpolating measures from the closest stations using

IDW. In our study area, three of the subregions each had two monitoring stations; the other seven had only one. Despite the fact that there might be inherent measurement error because water quality is approximated using the IDW approach, we think this approach improves the accuracy of the predicted water quality by accounting for distance from the monitoring stations.

To understand the effects of water quality on housing prices, we use the hedonic results to infer how residents perceive water quality. More specifically, residents' perceptions of water quality will influence the proper metric of water quality. Our statistical results compare different water quality metrics to infer how residents perceive water quality. The well-informed model assumes that homebuyers have comprehensive information about the quality of the water going back to 1999. Thus, we aggregate the data from the general water quality index to daily levels at each monitoring station and then further aggregate the water quality measurements to a summer level across all years up to (and including) the transaction year.

The myopic model uses the most recent five summer months prior to the purchase. For example, for a purchase made on June 2010, the water quality metric includes chlorophyll measures for May 2010, plus June–September 2009. The current month chlorophyll concentration data are not used since most homes enter contract at least 30 days prior to the actual transactions. We then assign each property to the closest water using ArcGIS. As indicate above, the "myopic" model is associated with a water quality impact on housing prices that decays rapidly over time. In contrast, the "well-informed" model is associated with a water quality impact that is more persistent over time. In order to differentiate the water quality information used by well-informed and myopic models, we compare the myopic model versus the well-informed model using data from 2002.

4. Estimation Results

4.1. Results for the Well-Informed Model

We first estimate separate semilog linear models with four percentile measurements—99th, 95th, 90th, and 50th—for the chlorophyll concentration during the summer for 2002 through 2013 using OLS (see Table 3). As indicated above, these different metrics for chlorophyll concentrations are used to identify whether buyers are more affected by rare but extreme environmental events, versus more typical water quality conditions. The distance dummy variables and interaction terms between distance and water quality in all four models show the expected signs and declining absolute magnitude as distance increases. The baseline category is houses located more than 1500 m from the shore of the bay. When homebuyers care more about the extreme events with highest chlorophyll concentration (99th percentile), we find that houses located within 100 m of the shore garner a 32.5% price premium over baseline homes (significant at the 1% level). As distance from the shoreline increases, the location premium consistently declines. The signs on our variables of interest—the interaction terms between chlorophyll concentration and distance dummy variables—

Table 3. Estimation Results for the Well-Informed Model Using OLS Under Four Water Quality Measures[a]

	log_price Chlorophyll Percentile			
Variable	99th (1)	95th (2)	90th (3)	50th (4)
Chlorophyll	0.0004** (2.034)	0.0006* (1.800)	0.0007 (1.509)	0.0008 (0.874)
Chlorophyll × distance dummy (less than 100 m)	−0.0010** (–2.309)	−0.0016** (–2.156)	−0.0024* (–1.787)	−0.0058 (–1.615)
Chlorophyll × distance dummy (100–750 m)	−0.0008* (–1.884)	−0.0012* (–1.881)	−0.0015 (–1.557)	−0.0023 (–1.193)
Chlorophyll × distance dummy (750–1500 m)	−0.0006 (–1.576)	−0.0010* (–1.749)	−0.0016** (–2.060)	−0.0040** (–2.532)
Distance dummy (less than 100 m)	0.325*** (8.720)	0.329*** (8.477)	0.338*** (8.936)	0.344*** (7.615)
Distance dummy (100–750 m)	0.156*** (2.966)	0.158*** (2.952)	0.161*** (2.870)	0.154*** (2.726)
Distance dummy (750–1500 m)	0.084*** (3.114)	0.086*** (3.220)	0.093*** (3.279)	0.099*** (3.358)
Observations	10,971	10,971	10,971	10,971
R^2	0.874	0.874	0.874	0.880
Adjusted R^2	0.873	0.873	0.873	0.876

[a]All of the models include controls for characteristics of the houses, lot size in hectares, square term of lot size, number of years since renovation, number of fire places, condition, living area in hundred square meters, square term of living area, number of bathrooms, number of half baths, air conditioning, pool, and dock, distance to the nearest highway exit in kilometers, and distance to downtown Providence in kilometers. We also control for neighborhood characteristics (median household income, population density, and people age 65 in the neighborhood), town fixed effects, and time fixed effects in the estimation. Robust *t* statistics are presented in parentheses. The asterisks (***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$) indicate level of significance.

Table 4. Estimation Results for the Well-Informed Model Using Spatial Models (Eight Nearest Neighbors) Under Four Water Quality Measures[a]

	log_price Chlorophyll Percentile			
Variable	99th (1)	95th (2)	90th (3)	50th (4)
Chlorophyll	0.0003* (1.934)	0.0004 (1.628)	0.0004 (1.413)	0.0001 (0.109)
Chlorophyll × distance dummy (less than 100 m)	−0.0006* (–1.874)	−0.0010** (–2.071)	−0.0017** (–1.982)	−0.0049** (–1.955)
Chlorophyll × distance dummy (100–750 m)	−0.0005** (–2.392)	−0.0008*** (–2.796)	−0.0010** (–2.219)	−0.0009 (–0.765)
Chlorophyll × distance dummy (750–1500 m)	−0.0005* (–1.853)	−0.0008** (–1.927)	−0.0012** (–2.283)	−0.0029** (–2.159)
Distance dummy (less than 100 m)	0.298*** (16.36)	0.301*** (16.23)	0.309*** (14.48)	0.320*** (12.71)
Distance dummy (100–750 m)	0.123*** (9.203)	0.126*** (9.323)	0.126*** (8.958)	0.118*** (7.730)
Distance dummy (750–1500 m)	0.068*** (5.248)	0.070*** (5.223)	0.074*** (5.405)	0.078*** (5.213)
Lambda (λ)	0.6168	0.6168	0.6169	0.6168
Std. Errs (λ)	0.0103	0.0103	0.0103	0.0103
loglikehood	2147.44	2149.23	2148.89	2148.85
AIC	−4170.9	−4174.5	−4173.8	−4173.7
Wald test	3577.5	3577.7	3574.2	3577.6

[a]All of the models include 10,971 observations and controls for characteristics of the houses, lot size in hectares, square term of lot size, number of years since renovation, number of fire places, condition, living area in hundred square meters, square term of living area, number of bathrooms, number of half baths, air conditioning, pool, and dock, distance to the nearest highway exit in kilometers, and distance to downtown Providence in kilometers. We also control for neighborhood characteristics (median household income, population density, and people age 65 in the neighborhood), town fixed effects, and time fixed effects in the estimation. Robust *t* statistics are presented in parentheses. The asterisks (***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$) indicate level of significance.

are negative and statistically significant as expected. These results indicate that poor water quality has a negative impact on prices for homes in relative close proximity to the shore and that the negative impact declines in magnitude as distance from the bay increases. In the 99th percentile specification, a one-unit increase in chlorophyll concentration leads to declines of 0.10% for homes within 100 m and 0.08% for homes 100–750 m and 0.06% for homes 750–1500 m from the shoreline. Regardless of the percentile for the chlorophyll concentration, the model shows that the impact of poor water quality diminishes with distance from Narragansett Bay. The positive coefficient on chlorophyll concentration in some models implies that higher water pollution levels is associated with higher prices of houses furthest from the shoreline. Although we refrain from interpreting this coefficient since it is quantitatively small and not statistically significant in the preferred models, one conjecture is that the coefficient reflects a market equilibrium effect, where higher pollution levels reduce demand for houses near the shoreline, increasing demand for substitute properties further from the shoreline. We also tested the model by dropping the data for the recession years (2007–2009) because it might be argued that the housing market was out of equilibrium during the recession so the basic assumptions of the hedonic model could be violated during those years. Our results appear qualitatively robust with respect to inclusion or exclusion of sales during the recession years (supporting information Table S3) and thus we employ the full data set for all analyses.

The results of the spatial (eight nearest neighbors) models for well-informed buyers are presented in Table 4. Overall, they point to a spatial threshold in the association between water quality and housing prices. The coefficient on chlorophyll concentration for the base category for distance is positive for all models but is not statistically significant for chlorophyll percentile 95%, 90%, and, 50%, i.e. poor water quality does not adversely affect the price of homes located more than 1500 m from shore. This result is consistent with *Dornbusch and Barrager* [1973], *Netusil et al.* [2014], and *Wolf and Klaiber* [2017], which found that water quality could affect the value of nonwaterfront properties up to 1 mi from the waterbody. Our results suggest that water quality likely has no significant effect on properties a mile or more from the shoreline.

When we account for spatial interactions and correlations among properties, the magnitudes of the coefficients are smaller than when we use OLS models. When we consider a chlorophyll concentration in the 99th percentile, the coefficient estimates for the interaction of water quality and distance are negative and significant. A one-unit increase in the chlorophyll concentration leads to a decline in price of 0.06% for homes within 100 m of the shore and declines of 0.05% for homes 100–750 m and 0.05% for homes 750–1500 m from the shore. The distance dummy variables are also decreasing with increasing distance from the shoreline. We find evidence of spatial dependence in all of the model specifications. Thus, ignoring spatial interactions and correlations will bias the results and overestimate the effect of water quality on housing

Table 5. Estimation Results for the Well-Informed Model Using OLS and Spatial Models With the 95th Percentile Water Quality Measures[a]

Variable	OLS Model	Spatial Model (Eight Nearest Neighbors)
Chlorophyll	0.0006* (1.800)	0.0004 (1.628)
Chlorophyll × distance dummy (<100 m)	−0.0016** (−2.156)	−0.0010** (−2.071)
Chlorophyll × distance dummy (100–750 m)	−0.0012* (−1.881)	−0.0008*** (−2.796)
Chlorophyll × distance dummy (750–1500 m)	−0.0010* (−1.749)	−0.0008** (−1.927)
Distance dummy (<100 m)	0.329*** (8.477)	0.301*** (16.23)
Distance dummy (100–750 m)	0.158*** (2.952)	0.126*** (9.323)
Distance dummy (750–1500 m)	0.086*** (3.220)	0.070*** (5.223)
R^2	0.874	
Adjusted R^2	0.873	
Lambda (λ)		0.6168
Std. Errs (ρ)		0.0103
Wald test		3577.7

[a]All of the models include controls for characteristics of the houses, lot size in hectares, square term of lot size, number of years since renovation, number of fire places, condition, living area in hundred square meters, square term of living area, number of bathrooms, number of half baths, air conditioning, pool, and dock, distance to the nearest highway exit in kilometers, and distance to downtown Providence in kilometers. We also control for neighborhood characteristics (median household income, population density, and people age 65 in the neighborhood), town fixed effects, and time fixed effects in the estimation. Robust t statistics are presented in parentheses. The asterisks (***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$) indicate level of significance.

prices. The results of the alternative spatial weight matrices (four and six nearest neighbors) are consistent with the results shown in Table 4.

4.2. Choosing the Best Well-Informed Model in Terms of the Water Quality Percentile

We use the maximum-likelihood search method to estimate the optimal nutrient-concentration percentile in our hedonic estimation. Since we assume that people are most concerned when the water quality is poor, all of the model specifications involve poor water quality—chlorophyll concentrations greater than or equal to the 50th percentile. Specifically, we run the model using different grid points (the 50th and 99th percentiles), identify the percentiles that have the highest values of likelihood, and then rerun the model using finer grid points, such as the 50th and 95th percentiles, until we find the optimum—the percentile that produces the highest likelihood value.

The maximum-likelihood search method finds that the best fit for the water quality metric is the 95th percentile in both the OLS and the spatial models regardless of the number of nearest neighbors used (four, six, and eight). This result provides evidence that extreme water quality events appear to have the greatest impact on housing prices. This is consistent with a hypothesis that housing prices are most impacted by rare but highly discernable events, such as algal blooms, odors, and fish kills. Results from the OLS model and the spatial regression using eight nearest neighbors for the 95th percentile are shown in Table 5.

When we compare the OLS and spatial models for the 95th percentile of water quality, we find smaller magnitudes for the interaction terms for water quality and distance in the spatial model while the levels of significance are about the same for both. For instance, a one-unit increase in the chlorophyll concentration leads to declines in price of 0.10%, 0.08%, and 0.08% for properties located within 100 and 100–750 and 750–1500 m away from the shoreline, respectively. Furthermore, the coefficients of the distance dummy variables in the spatial error model are also smaller than the ones in the OLS model.

4.3. Results for the Myopic Model

The results from the myopic models for the four percentiles of water quality are presented in Table 6. We estimate separate semilog linear models for each measurement of water quality for the transaction summer. Relative to the well-informed models, the water quality and distance interaction terms in the myopic models are positive but not significant for different metrics for chlorophyll concentrations (models 1–4) for houses within 100 m of the shoreline, 100–750, 750–1500 m compared to the base category (houses more than 1500 m from the shore). It indicates that the impact of water quality does not change over distance. Furthermore, the magnitudes of the interaction terms did not decrease with distance from the water, which also contradicts the results of the well-informed model (Table 3). Notably, the water quality indicator, chlorophyll concentrations have positive and significant impacts (at 1% level) on housing prices (models 1 and 2), which are

Table 6. Estimation Results for the Myopic Model Under Four Water Quality Measures[a]

	log_price			
	Chlorophyll Percentile			
Variable	99th (1)	95th (2)	90th (3)	50th (4)
Chlorophyll	0.0002*** (2.848)	0.018*** (2.775)	0.0001 (0.937)	0.240 (1.325)
Chlorophyll × distance dummy (less than 100 m)	0.0006 (0.506)	0.175 (1.034)	0.003 (1.090)	0.164 (0.423)
Chlorophyll × distance dummy (100–750 m)	−0.0002 (−0.849)	−0.013 (−0.639)	−0.0001 (−0.087)	−0.252 (−0.726)
Chlorophyll × distance dummy (750–1500 m)	0.0001 (0.180)	0.013 (0.452)	0.0003 (1.214)	−0.122 (−0.489)
Distance dummy (less than 100 m)	0.297*** (4.688)	0.259*** (3.668)	0.255*** (3.746)	0.303*** (6.301)
Distance dummy (100–750 m)	0.164*** (3.567)	0.156*** (3.530)	0.155*** (4.052)	0.184*** (3.253)
Distance dummy (750–1500 m)	0.112** (2.382)	0.109*** (2.608)	0.103*** (2.689)	0.130** (2.475)
Observations	5495	5495	5495	5495
R^2	0.777	0.777	0.778	0.777
Adjusted R^2	0.775	0.775	0.775	0.775

[a]All of the models include controls for characteristics of the houses, lot size in hectares, square term of lot size, number of years since renovation, number of fire places, condition, living area in hundred square meters, square term of living area, number of bathrooms, number of half baths, air conditioning, pool, and dock, distance to the nearest highway exit in kilometers, and distance to downtown Providence in kilometers. We also control for neighborhood characteristics (median household income, population density, and people age 65 in the neighborhood), town fixed effects, and time fixed effects in the estimation. Robust *t* statistics are presented in parentheses. The asterisks (***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$) indicate level of significance.

counterintuitive. It means the worse of water quality, the higher the housing prices. Realistically, buyers would not reasonably prefer to live less than 100 m from a heavily contaminated body of water that is unnaturally green, gives off unpleasant odors, and/or has been overtaken by algal blooms. Whereas, results from models 3 to 4 show that the impact of poor water quality does not have influence on housing prices in Narragansett Bay.

In terms of a proximity effect, the distance dummy variables from the models (1–4) point to a consistent positive impact from proximity to the water. We find that houses located within 100 m of the shore adds a 29.7%, price premium (model 1) compared to 25.9%, 25.5%, and 30.3%, respectively, relative to houses more than 1500 m from the shore (models 2–4). We also find that all four models show consistency in the declining absolute magnitude as distance increases.

The spatial tests for the myopic models again confirm that the spatial error model with eight nearest neighbors is the most appropriate specification, and once again the results are counterintuitive. The full results for the spatial myopic models (using eight nearest neighbors) are shown in supporting information Table S11.

As in the well-informed model, the maximum-likelihood grid search in the myopic model indicates that extreme water quality conditions are the most influential in determining housing prices, and the 90th percentile chlorophyll concentration fits the hedonic estimation best. Table 7 compares the results of the OLS and spatial models using the 90th percentile water quality measures. We find that the magnitudes of the interaction terms are smaller in all of the spatial models and that the significance levels are smaller.

Notably, the results of the spatial myopic models for the impact of water quality contradict most earlier studies of the effect of water quality on property prices [*Gibbs et al.*, 2002; *Leggett and Bockstael*, 2000; *Netusil et al.*, 2014; *Poor et al.*, 2001; *Walsh et al.*, 2011]. Additionally, the particular form of the specification of environmental quality can be important. We compared the preferred "myopic" model to the "well-informed" model and found the "well-informed" model has water quality variables with coefficients that are statistically significant, of the expected sign, and that make a considerable contribution to explanatory power of the regression equation. Combined with its consistency with prior studies and goodness of fit, the well-informed model performs better than the myopic model, and the remainder of the discussion addresses only the well-informed model.

5. Scenario Analysis and the Implicit Value of Water Quality

We analyze scenarios to predict the components of benefits of improved water quality that are capitalized into housing prices under several hypothetical water management programs for the upper portion of the Bay. It is important to note that this is one of a number of categories of water quality benefits, including recreational uses and nonuse values. Hence, the results likely to understate the full range of benefits of water quality improvements.

Table 7. Estimation Results for the Myopic Model Using OLS and Spatial Models With the 90th Percentile Water Quality Measures[a]

Variable	OLS Model	Spatial Model (Eight Nearest Neighbors)
Chlorophyll	0.0001 (0.937)	0.0001 (0.930)
Chlorophyll × distance dummy (<100 m)	0.003 (1.090)	0.0013 (0.956)
Chlorophyll × distance dummy (100–750 m)	−0.0001 (–0.087)	−0.0001 (–0.137)
Chlorophyll × distance dummy (750–1500 m)	0.0003 (1.214)	0.0004 (1.373)
Distance dummy (<100 m)	0.255*** (3.746)	0.168*** (3.961)
Distance dummy (100–750 m)	0.155*** (4.052)	0.084*** (6.213)
Distance dummy (750–1500 m)	0.103*** (2.689)	0.057*** (4.698)
R^2	0.778	
Adjusted R^2	0.775	
Lambda		0.594***
Std. Err.		0.015
Wald test		1503.4***

[a]All of the models include controls for characteristics of the houses, lot size in hectares, square term of lot size, number of years since renovation, number of fire places, condition, living area in hundred square meters, square term of living area, number of bathrooms, number of half baths, air conditioning, pool, and dock, distance to the nearest highway exit in kilometers, and distance to downtown Providence in kilometers. We also control for neighborhood characteristics (median household income, population density and people age 65 in the neighborhood), town fixed effects, and time fixed effects in the estimation. Robust *t* statistics are presented in parentheses. The asterisks (***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$) indicate level of significance.

The most prominent scenario is a nitrogen intervention that leads to a 25% reduction in the chlorophyll concentration and is based on the Phase I prototype of the Narragansett-3VS model [*Industrial Economics Inc. et al.*, 2012]. The intervention is comprised of six actions implemented gradually between 2010 and 2050: a 50% reduction in loadings from WWTFs' 2014 level; upgrading of 50% of the independent sewage disposal systems; 50% reductions in loadings from atmospheric deposition, livestock, and agricultural fertilizer from their respective baselines; and low-impact development after 2014 [*Industrial Economics Inc. et al.*, 2012]. *Industrial Economics Inc. et al.* [2012] first tested and simulated water quality using the Narragansett-3VS model and found that nitrogen interventions would reverse the upward trend in nitrogen from atmospheric deposition and greatly reduce nitrogen loadings from the baseline by 2050. Furthermore, their results demonstrated that the corresponding nitrogen concentration in the water would be reduced by about 50% by 2050.

To reflect corresponding changes in chlorophyll concentration in our coastal water quality indicator, we followed *Dettmann et al.* [2004] in modeling the effect of nitrogen loading on chlorophyll concentrations. Since the impact of chlorophyll is much greater during the summer when water temperatures are high, we adopt *Dettmann et al.* [2004] summer formula for chlorophyll concentrations:

$$Chlorophyll\ \ a=57.5\times(Nitrogen\ \ concentration\ \ in\ \ water)^{2.09} \tag{5}$$

which suggests that a 57.5% reduction in nitrogen concentration is roughly equal to a 25% reduction in chlorophyll concentration.

We also include 10%, 50%, and 75% reductions in the chlorophyll concentration (that correspond to nitrogen reductions of 33%, 72%, and 87%, respectively). We use a 75% reduction as the high end of water quality improvement because a reduction in chlorophyll of roughly 75% could bring the Seekonk River in Rhode Island to the threshold for good water quality [*Rohr*, personal communication, 2014]. Note that these are purely hypothetical scenarios intended to represent a range of water quality projects from relatively modest to ambitious and should not be viewed as recommendations or even as feasible goals.

We compare each chlorophyll reduction to a status-quo baseline. To properly estimate the discounted value of benefits from complex programs that are implemented over time, we would need to simulate the rate of improvement in water quality over time, and calculate the present value of benefits for the time path of water quality improvement for each different set of programs. Doing so is beyond the scope of this analysis. Instead, we simplify the process of simulation, by assuming an immediate full reduction in chlorophyll at all Narragansett Bay monitoring sites simultaneously and that the housing market equilibrium remains stable.

Table 8. Number of Actual Houses by Water Quality Region

	Water Quality Region					
Distance	Phillipsdale	Bullock's Reach	Conimicut Point	North Prudence	Sally Rock	Greenwich Bay
Less than 100 m	106	1,619	755	236	629	340
100–750 m	5,769	8,588	5902	2082	2115	2,213
750–1500 m	9,084	5,986	741	612	317	4,032
Greater than 1500 m	23,224	13,786	0	12	0	11,878
Total	38,183	29,979	7398	2942	3061	18,463

We use the well-informed model and a 95th percentile chlorophyll concentration as the water quality measure to examine the impacts of the nitrogen interventions on housing prices. Ideally, we would use actual counts and characteristics of houses in the coastal towns and cities in the study area to measure welfare changes. However, because there is limited information on characteristics of the houses, we identify a representative house for each distance radius in a given water quality subregion by taking averages for the characteristics from all of the property transactions in the same distance radius and water quality subregion. The number of actual houses in each water quality subregion of the Upper Bay is shown in Table 8.

5.1. Simulation Results for Individual and Aggregated Welfare Changes

The potential benefits of a property being located near Narragansett Bay are expected to increase with water quality. To facilitate the welfare measurements, we assume that the hedonic price function does not change and that the change in water quality does not affect the cost to builders of supplying housing amenities [*Freeman et al*., 2014]. We acknowledge that hedonic price function measures marginal effects only, not the bid function [*Freeman et al*., 2014]. This means our estimates of nonmarket water quality effects are, in effect, approximations to the true measures for nonmarginal water quality changes. Table 9 shows estimates of the individual and aggregate benefits for all water quality subregions in upper Narragansett Bay

Table 9. Individual and Aggregate Benefits for Chlorophyll Reduction for the Subregions Using a 95th Percentile Measure

		Individual Benefit in Thousand Dollars			Aggregate Benefit in Million Dollars			
Water Region	Chl Concentration Reduction (%)	Less than 100 m	100–750 m	750–1500 m	Less than 100 m	100–750 m	750–1500 m	Total Aggregate Benefit in Million Dollars
Phillipsdale	10	0.19	0.18	0.17	0.02	1.04	1.54	2.60
	25	0.48	0.45	0.43	0.05	2.60	3.91	6.55
	50	0.95	0.90	0.86	0.10	5.19	7.81	13.11
	75	1.43	1.36	1.29	0.15	7.85	11.72	19.72
Bullock's Reach	10	0.20	0.20	0.19	0.32	1.72	1.14	3.18
	25	0.52	0.49	0.47	0.84	4.21	2.81	7.86
	50	1.03	0.98	0.95	1.67	8.42	5.69	15.77
	75	1.54	1.47	1.42	2.49	12.62	8.50	23.62
Conimicut Point	10	0.49	0.50	0.42	0.37	2.95	0.31	3.63
	25	1.25	1.25	1.04	0.94	7.38	0.77	9.09
	50	2.49	2.51	2.08	1.88	14.81	1.54	18.24
	75	3.72	3.75	3.11	2.81	22.13	2.30	27.25
North Prudence	10	3.57	2.28	1.45	0.84	4.75	0.89	6.48
	25	8.88	5.69	3.62	2.10	11.85	2.22	16.16
	50	17.69	11.33	7.21	4.17	23.59	4.41	32.18
	75	26.41	16.92	10.76	6.23	35.23	6.59	48.05
Sally Rock	10	0.17	0.07	0.07	0.11	0.15	0.02	0.28
	25	0.43	0.18	0.18	0.27	0.38	0.06	0.71
	50	0.86	0.36	0.36	0.54	0.76	0.11	1.42
	75	1.30	0.55	0.54	0.82	1.16	0.17	2.15
Greenwich Bay	10	0.28	0.29	0.33	0.10	0.64	1.33	2.07
	25	0.71	0.74	0.81	0.24	1.64	3.27	5.14
	50	1.41	1.47	1.62	0.48	3.25	6.53	10.26
	75	2.12	2.21	2.44	0.72	4.89	9.84	15.45
All stations	10	4.9	3.52	2.63	1.76	11.24	5.23	18.24
	25	12.27	8.8	6.55	4.44	28.05	13.03	45.52
	50	24.43	17.55	13.08	8.84	56.03	26.10	90.97
	75	36.52	26.26	19.56	13.22	83.88	39.12	136.23

10.1002/2016WR019606

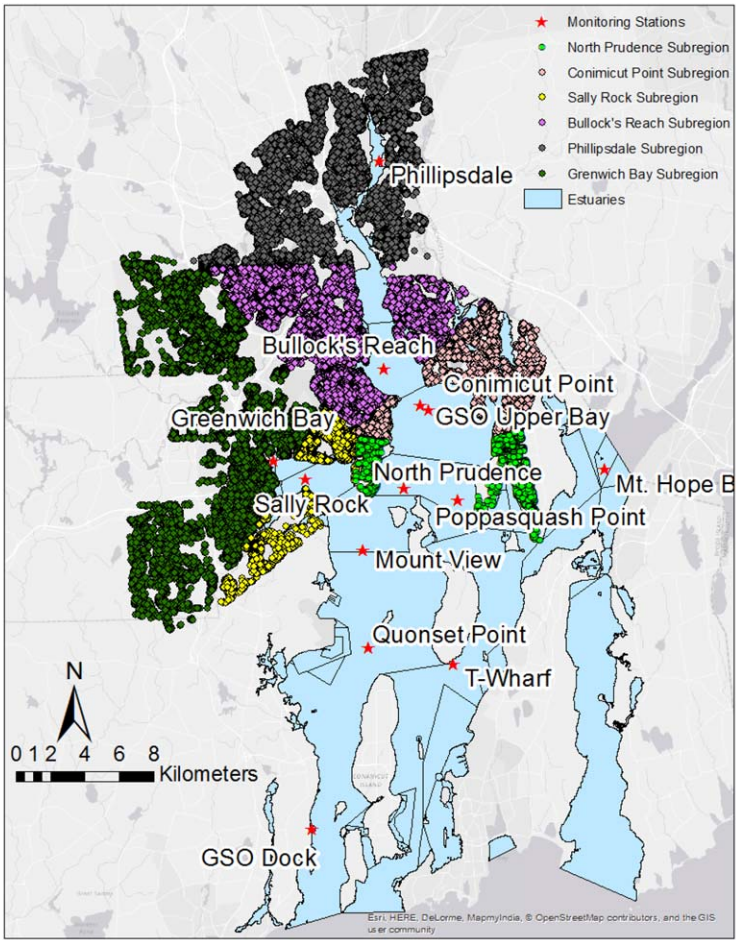

Figure 3. Single-family houses in each water quality subregion that can benefit from water quality improvement in upper Narragansett Bay.

using the 95th percentile measure. The benefits in most of the subregions decline with increasing distance to the shoreline. Additionally, benefits increase with larger water quality improvements. The Phillipsdale subregion has some of the worst water quality. The individual benefit of a 10% reduction in chlorophyll relative to the baseline for homes in that subregion within 100 m of the shoreline is about $190 per house. However, the benefit per house increases by only about $180 and $170 for houses in the 100–750 and 750–1500 m radiuses. If the nitrogen reduction intervention was successfully implemented and the chlorophyll concentration was reduced by 25% by 2050, the average price of a home would increase within 100 m of the shore by $480. The price would increase $450 for a representative house located 100–750 m from the shoreline and $430 for a house located 750–1500 m.

The aggregate benefit by subregion is calculated using actual counts of houses provided by E-911 (enhanced emergency service) point data as of March 2014 that include physical addresses for all buildings and other significant infrastructures in Rhode Island [*Rhode Island Geographic Information System*, 2014]. In line with our hedonic price models, we use the data on single-family homes to estimate aggregate benefits for sales prices for homes in each subregion (Figure 3). Using the individual benefit in sale price for a representative house located within a particular distance radius of a water quality subregion and the number of houses located in the subregion (see Figure 3 and Table 8), we can estimate the aggregate benefit for the subregion (see Table 9).

Under a 25% reduction in chlorophyll concentrations in all of the subregions, we find an aggregate increase in housing prices of about $45.52 million. The benefit varies by subregion and distance radius. For example, the Bullock's Reach and Greenwich Bay subregions benefit by $7.86 million and $5.14 million, respectively. In Bullock's Reach, houses located 100–750 m away benefit most at $4.21 million relative to homes at other distance radiuses. In Greenwich Bay, houses 750–1500 m away benefit most from the 25% reduction. When discounting and timing of water quality cleanup are accounted for, the present benefits of the 25% chlorophyll concentration reduction scenarios are as follows in Table 10. For example, if the 25% chlorophyll concentration reduction goal can be achieved in year 2017, the present benefits will be $45.52 million. However, if the goal can be achieved in additional 5 or 10 years later or year 2050, the present value of benefits discounted to the year of 2017 will be $39.3, $33.9, and $17.2 million if 3% discount rate is used. If 7% discount rate is considered, then the present value of benefits discounted to the year of 2017 will be $32.5, $23.1, and $4.9 million, respectively. Notably, the magnitudes of the aggregate benefits could

Table 10. Total Aggregated Present Value of Benefits Discounted to the Year of 2017 Under 25% Chlorophyll Concentration Reduction Scenario

	Total Aggregated Benefits in Million Dollars			
Discount Rate (%)\Year Achieved	2017	2022	2027	2050
3	45.52	39.27	33.87	17.16
5	45.52	35.67	27.95	9.10
7	45.52	32.45	23.14	4.88

be significantly different when using other percentile measures of the original water quality, which emphasizes the importance of the measures chosen when valuing environmental goods and services. Two levels of water quality degradation measures, for example, could produce significantly different valuations.

6. Conclusion and Discussion

This study examines the impact of reductions in nutrient loads and improved water quality on the price of homes located near Narragansett Bay using a hedonic housing price method. Unlike previous studies that treated estuaries as static bodies of water, our study examines different levels of water quality measures represented by the concentration of chlorophyll, which correlates with easily observable water quality characteristics such as color and odor and can lead to algal blooms when the concentration is extremely high. We compiled data on water quality measurements taken every fifteen minutes at fixed and buoy monitoring sites on Narragansett Bay from 1999 through 2013 and matched it to detailed data on housing transactions to assess the impacts of water quality on housing prices.

As expected, there is a price premium for homes located within a mile of Narragansett Bay. We consistently find, however, that poor water quality in the bay reduces the price of such homes with the greatest impact on houses closest to the shoreline. The results show that the magnitudes of the estimated parameters for both the impact of proximity and the interaction of proximity with water quality vary depending on the water quality metric used for chlorophyll concentration. At the median concentration (the 50th percentile), the differences in the coefficient estimates and potential benefits are relatively large, suggesting people's perception on water quality and corresponding water quality measures chosen for valuation studies can make a considerable difference in the marginal implicit prices associated with marginal changes in water quality.

Unlike previous studies, which mostly used median or average measures of water quality, we investigated buyers' perceptions of water quality by testing the average measures versus extreme events. We also compared the "well-informed" model which includes the historical data on water quality to a "myopic" model which focus only on water quality in the most recent year. This can be interpreted as providing an analysis of two specifications for persistence of water quality impacts on housing prices. The myopic model is consistent with a 1 year decay, so that housing prices only reflect water quality from the previous year. The "well-informed" model reflects an impact of water quality that is more persistent over time, so that housing prices reflect water quality over a longer period of time.

The results of the well-informed model find the best fit for the 95th percentile of chlorophyll levels (the myopic model find the best fit for the 90th percentile of chlorophyll levels), suggesting that housing prices are more likely to be impacted by extreme environmental events, rather than typical water quality conditions. This is consistent with housing prices reflecting highly visible events, such as algal blooms, odors, and fish kills. Policymakers can integrate a better understanding of buyers' perceptions of and responses to water quality issues into their efforts to prevent contamination of waterbodies and remediate damage that does occur.

Spatial tests show that the existence of spatial autocorrelation and the spatial error model outperformed the spatial lag model. Furthermore, the results from the spatial error models using three specifications of the matrix (four, six, and eight nearest neighbors) are consistent. We also find that the well-informed model outperformed the myopic model reflecting a slower decay rate over time for the effect of water quality on housing prices.

We analyze a scenario involving current efforts to reduce nitrogen in Narragansett Bay by requiring developments to be low-impact, upgrading independent sewage disposal systems, and reducing loadings from atmospheric deposition, livestock production, and agricultural fertilizer. We model a 25% reduction with a 95th percentile chlorophyll concentration measure to identify potential benefits for the housing market near the coast of the bay and find an increase in the aggregate value of homes in all coastal municipalities of about $45.5 million. Since uncertainty is associated with the effects of extreme water quality events, decision-makers should be cognizant of the negative effects of climate change on water quality in Narragansett Bay in terms of home prices.

Although this study provides substantial evidence that home prices in communities along Narragansett Bay rise in response to improved water quality, several caveats must be kept in mind. First, we do not account for the dynamics between changes in supply and demand corresponding to the change in water quality. In reality, the hedonic housing-price functions will shift in response to changes in water quality, and water quality preferences may change over time. However, our approach only approximates the true welfare changes [*Freeman et al*., 2014]. We also do not account for benefits from improved water quality other than those capitalized into the value of homes near the shoreline. So for example, our estimates exclude recreational use by people who live farther from the bay, the nonuse values, and the economic benefits associated with recovery of Rhode Island's fishery industry, etc. Future studies could take a more general approach to exploring the relationship between the distribution of water quality parameters and housing prices and thereby more accurately simulate the effects of a policy. For example, instead of specifying percentiles for the chlorophyll concentration, one could estimate the shape and scale parameters of the gamma distribution for each monitoring station, which could shift in response to the nutrient reduction program. We would like to examine the changing environmental values over times in the future research.

Despite some limitations, our analysis provides a useful example and simplified illustration of the potential benefits of improved water quality for the price of homes located near Narragansett Bay. The hedonic approach to housing prices captures the marginal benefits of changes in water quality that are capitalized into home values. Our results are valuable for policymakers interested in prioritizing areas for intervention and remediation as we find the buyers are most concerned about extreme degradation of water quality and consider water quality historically rather than reacting solely to the current situation.

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