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Analysis

Coupling Natural and Human Models in the Context of a Lake Ecosystem: Lake Mendota, Wisconsin, USA

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ABSTRACT

Nutrient loading lead to poor water quality and this has impacts of the welfare of people who live near lakes. We develop a novel coupling between a limnology model of within-lake hydrodynamics and an economic model of property prices to support integrated assessments of actions to protect or improve water quality. We find, in the context of Lake Mendota that is eutrophic with high concentrations of nitrogen (N) and phosphorous (P), that there is a nonlinear response in water quality to changes in nutrient loading. Reductions in nutrient loading result in much larger improvements in water quality than the magnitude of water quality deterioration with a similar size increase in nutrient loading. Given the in-situ concentrations of N and P in the lake, large reductions in nutrient loading are required to have a substantial impact on water quality.

1. Introduction

Lakes support a myriad of ecosystem services that benefit humans and have quantifiable economic effects, including the provisioning of drinking water and recreational activities, such as swimming, fishing, and boating. These services can be compromised by poor water quality, which commonly occurs when lakes are impacted by excessive nutrient inputs from nonpoint source pollution such as phosphorus and nitrogen from agricultural runoff. High nutrient loads fuel algal blooms, which can lead to toxin production, decreased water transparency, and low oxygen levels (hypoxia) (Brookes and Carey, 2011). Economic consequence of surface water quality degradation on nearby residential properties and water-based recreation are well known (David, 1968; Boyle et al., 1999; Poor et al., 2007; Walsh and Milon, 2016; Wolf and Klaiber, 2017; Zhang and Sohngen, 2018; and Nicholls and Crompton (2018) for summary of the literature). Likewise, the linkage between nutrient loading and lake water quality is well documented in the limnological literature (e.g., Edmondson, 1970; Vollenweider et al., 1974; Schindler, 1977). However, the full set of linkages from nutrient loading to changes in lake water quality to property values has yet to be fully explored. In this study, we couple lake ecosystem and economic models to examine the relationship between upstream cause (nutrient loading) and downstream consequence (property value changes) as mediated by lake water quality changes. An understanding of these complex dynamics is critical to support effective and efficient policies that target water quality improvements to mitigate the social costs of aquatic ecosystem degradation.

Some coupled models have been developed to support integrated assessments of surface water quality. These studies have typically coupled a SWAT model (Soil and Water Assessment Tool, https://swat.tamu.edu) with an economic decision making model (e.g., Jha et al., 2007; Secchi et al., 2007; Liu et al., 2019). These studies typically use SWAT to model the fate-transport of nutrients based on land-use practices to understand the impact on water quality. Here, given a specified level of nutrient loading, the limnological model calibrates the impact on the lake ecosystem which is then passed to the economic model.

To our knowledge, this paper presents the first coupling of a model of lake dynamics with a hedonic property-value model to support integrated assessments of the effects of different nutrient loading

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scenarios on lake water quality and consequently property values (see Kling et al., 2017). To do so, we couple a whole-ecosystem lake model (General Lake Model, hereafter GLM; Hipsey et al., 2017) to a hedonic property-value model (hereafter hedonic model) to link changes in lake nutrient loading into changes in lakefront property values (Taylor, 2017). The GLM model has been stress tested across 32 lakes selected from a global observatory network (Bruce et al., 2018) and calibrated to observed data from Lake Mendota. The hedonic model is estimated using observed water-quality data from Lake Mendota. We use GLM to model lake water quality responses under different nutrient loading scenarios and use GLM outputs as inputs to the hedonic model to compute changes in capitalized property values under the different nutrient loading scenarios. We then consider how capitalized changes in property values impact property tax revenues to consider effects on members of the community that do not own property on or near the lake.

This research makes several important contributions: first, it advances scientific knowledge at the intersection of natural processes and human choices in the context of lake ecosystems. In Lake Mendota with compromised water quality, reducing nutrient loads has a much greater positive impact than the negative impact of increases in nutrient loads. Second, given the in-situ concentrations of nutrients in the lake, large reductions in nutrient loading are required to have a substantial impact on water quality and thereby property values. Third, changes in property values are not experienced by all households in a lake community and this paper considers resulting changes in property-tax revenues from affected lakefront properties that have a ripple effect across the community through changes in municipal budgets (Brunori et al., 2006). Fourth, the model coupling provides an important evidence-based linkage so that economic predictions of changes in capitalized property values are directly linked to the changes in non-point source pollution loading to a lake (e.g., Phaneuf, 2002). Collectively, analytical results based on this type of coupled modeling inform and reduce uncertainty in identifying effects and quantifying benefits and cost of policies to protect and enhance freshwater resources (Bosch et al., 2006; Keeler et al., 2012).

2. Methods and Data

We use Lake Mendota (Madison, Wisconsin, USA; Fig. 1) as a case study for exploring relationships between nutrient loading, water quality, property values, and tax revenues. Mendota is a north temperate lake that is eutrophic with continuing high levels of nutrient loading. As part of the North Temperate Lakes Long-Term Ecological Research (NTL-LTER) program (Carpenter et al., 2007), long-term and high-frequency physical, chemical, and biological data are available to calibrate GLM and estimate the hedonic model (Brock, 2012). Lake Mendota has a surface area of 40 km^2, mean and maximum depths of 12.8 m and 25.3 m, respectively, a mean water residence time of 4.3 years, and is ice-covered each winter (December–January through March–April) (Lathrop and Carpenter, 2014). A combination of agricultural (67% of the watershed) and urban (22% of the watershed) land uses in the watershed contribute to high loading of nitrogen (N) and phosphorus (P) to the lake (Bennett et al., 1999; Lathrop, 2007; Duffy et al., 2018). As a result, Lake Mendota experiences annual summer phytoplankton blooms that result in noxious odors, surface scums, and beach closures (Carey et al., 2016). There is year-to-year variability in the magnitude of the blooms, which is linked to total precipitation and variation in water temperature (Lathrop and Carpenter, 2014; Carey et al., 2016).

In this section, we outline the structure and calibration of the GLM, which we use to simulate changes in lake water quality in response to changes in nutrient loading. We then describe the estimation of the hedonic model that links changes in lake water quality with changes in property values. Finally, we discuss coupling the models to consider the effects of changes in nutrient loading on property values and property tax revenues (Fig. 2).

2.1. General Lake Model (GLM)

GLM is an open-source, one-dimensional hydrodynamic model that uses dynamic vertical layers to simulate water and energy budgets within a lake (Hipsey et al., 2014, 2017). GLM is coupled with the Aquatic EcoDynamics library (GLM-AED version 2.2.0; Hipsey et al., 2013) to model vertically-resolved, dynamic water quality metrics, including light attenuation and concentrations of dissolved oxygen, nitrogen (N), phosphorus (P), and chlorophyll-a (chl-a; a proxy for phytoplankton biomass). We ran the model at a daily time step over a 13.5-year period, from April 1, 2000 to December 31, 2013 to simulate seasonal dynamics and inter-annual variability, including both high (e.g., 2008) and low precipitation years (e.g., 2001–2003).

2.1.1. GLM Driver Data

GLM requires both meteorological and surface water inflow time series as driver data. We compiled meteorological data at an hourly time step from the North American Land Data Assimilation System (NLDAS-2; Cosgrove et al., 2003) that included air temperature, short and long wave radiation, relative humidity, wind speed, and precipitation (rain and snow).

Surface water inflow time series required discharge (flow volume), water temperature, and concentrations of N (nitrogen) and P (phosphorous) at daily time steps. We separated inflow N concentrations into fractions for inorganic N as nitrate (NIT; NO_3) and ammonium (AMM; NH_4), and dissolved organic nitrogen (DON). We separated inflow P concentrations into fractions for inorganic P as filterable reactive phosphorus (FRP) and FRP adsorbed to particles (FRP_ads), and organic P as both dissolved (DOP) and particulate (POP) fractions.

Continuous discharge, temperature, and nutrient time series were not available for the entirety of the Lake Mendota watershed from 2000 to 2013. To address this challenge, we produced modeled hydrological time series by combining mechanistic hydrological modeling for spatially resolved inflow with regression modeling for solute fluxes. For the former, we used the Pennsylvania Integrated Hydrological Model (PIHM; Kumar et al., 2009) to model surface inflow discharge at a daily time-step from 2000 to 2013. PIHM-modeled discharge included six hydrological inflows: Yahara River (23% of inflow), Pheasant Branch River (4%), Spring Harbor (2.3%), Six Mile Creek (8.4%), overland flow (62%), and groundwater (0.2%). To match available USGS gauge data, we combined these into two inflows. Pheasant Branch and Spring Harbor were treated as one inflow, and the four remaining inflows (Yahara River, Six Mile Creek, overland flow, and groundwater flow) were combined into one Yahara inflow. Water temperature time series for both inflows (Pheasant Branch and Yahara) were available from the same USGS gauges at which nutrient concentration data were collected.

We built regression models using discharge and surface nutrient concentrations from USGS gauges on two Lake Mendota inflows: Yahara River at Windsor (USGS gauge 05427718) and Pheasant Branch (USGS gauge 05427948). For the Yahara River inflow, total phosphorus (TP; the sum of organic and inorganic fractions) data were available for the entire model period (2000 − 2013), whereas nitrogen data (NIT: nitrite + nitrate, Kjeldahl: ammonia + organic nitrogen) were available from 2015 to 2017. For Pheasant Branch, data for both N and P concentrations were available beginning in 2015. We built regression models for TP, NIT, and Kjeldahl nitrogen (dissolved and particulate organic N + AMM) at the Yahara and Pheasant Branch rivers using the *loadflex* package in R (Appling et al., 2015). We then used these regression models to predict N and P concentrations in the Yahara and Pheasant Branch using discharge time series from the PIHM model output.

Following Snortheim et al. (2017), we doubled TP concentrations to include an adsorbed fraction not measured in the field. We then calculated concentrations of each phosphorus species (FRP, FRP_ads, DOP,

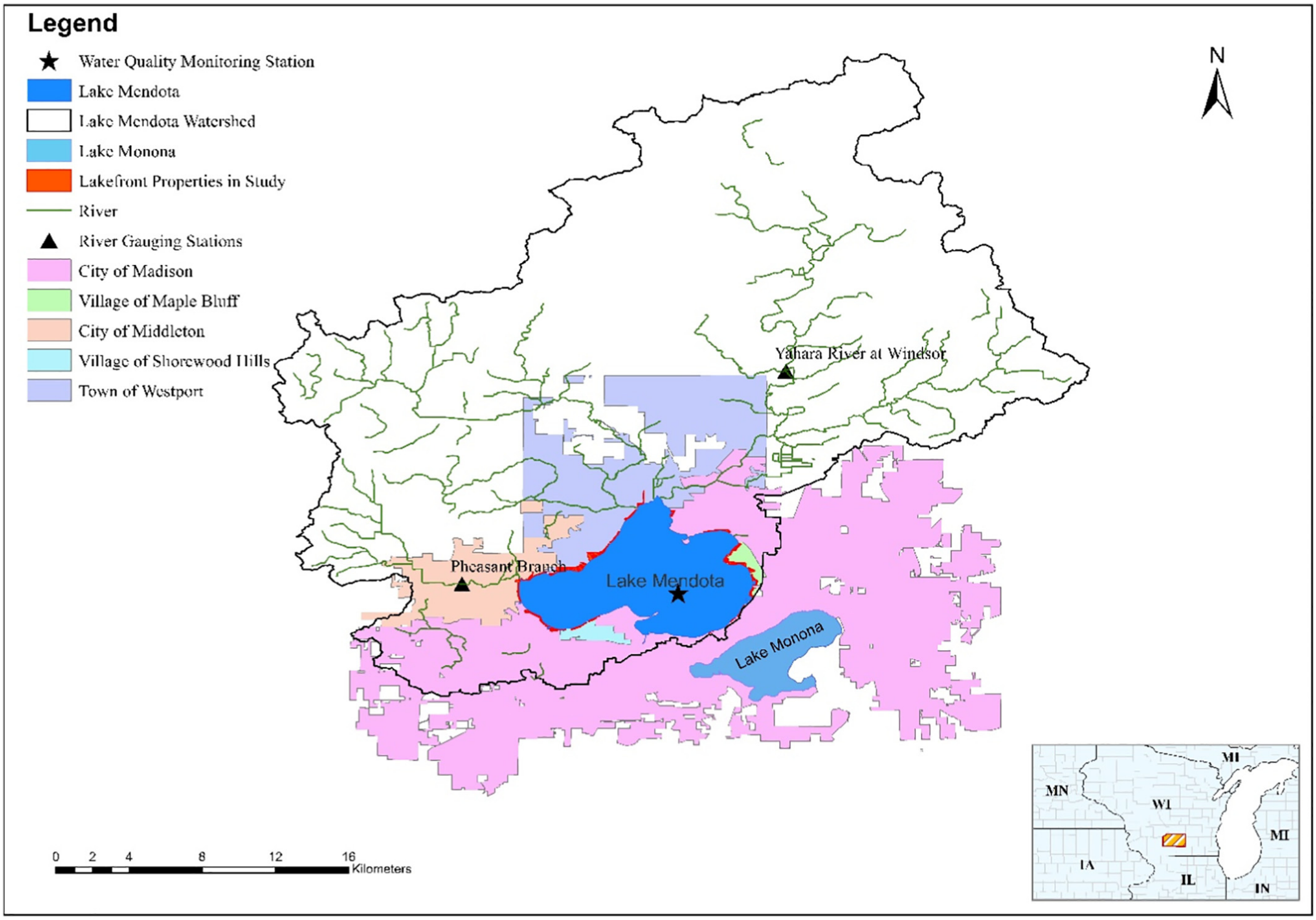

Fig. 1. Map of the study area. Lower right panel denotes the location of Dane County, WI, within which the Lake Mendota catchment (Latitude: 43.09, Longitude: −89.40) is located.

POP) for each of the two inflows as fractions of TP as follows, approximated from values reported by USGS for the gauging stations: 0.235 FRP, 0.500 FRP_ads, 0.195 DOP, and 0.070 POP. We calculated concentrations of DON, NIT, and AMM for each of the two inflows as fractions of Kjeldahl nitrogen as follows, approximated from values reported by USGS for the gauging stations and with the assumption that a small fraction of the Kjeldahl nitrogen was DON: 0.076 DON, 0.167 AMM, 0.757 NIT.

2.1.2. GLM Calibration and Validation

The underlying equations of GLM include many parameters that can be calibrated to reflect conditions in a specific lake. We calibrated parameters for the Lake Mendota GLM using results from Hart et al. (2017a, 2017b) as initial values, and then adjusted the parameters following the procedures described below.

The 8-year model calibration period ran from 2001 to 2010, and the validation period ran from 2011 to 2013. For calibration, we calculated goodness-of-fit (GOF) metrics involving the comparison of model outputs of maximum water temperature, mean dissolved oxygen, and mean chl-a concentrations to observed high-frequency buoy and manually collected data from the NTL-LTER. We manually adjusted model parameters to sequentially optimize GOF for these model state variables with a focus on capturing seasonal patterns and peak timing for each state variable. We calculated four GOF metrics for state variables at the lake surface (0–4 m) using the *hydroGOF* package for R (Zambrano-Bigiarini, 2017): the coefficient of determination (R^2), root mean square error (RMSE), Spearman's rank correlation coefficient (Spearman's rho [ρ]), and normalized mean absolute error (NMAE; Kara et al., 2012). Appendices A1–A6 present the parameter sets used in the calibrated baseline model. The calibrated baseline GLM adequately represented the focal calibration state variables over the model time period (Table A7), with GOF values similar to those of previously published Lake Mendota ecosystem models (e.g., Kara et al., 2012; Snortheim et al., 2017).

2.1.3. GLM Water Quality Outputs

GLM produces output variables that capture diverse aspects of lake water quality, many of which may not be known to, nor are easily observed by, property sellers and buyers. In this analysis, we focused on two key water quality metrics for inclusion in the hedonic model, namely water clarity and surface chl-a concentrations. We chose these two metrics because they have been shown by the economic literature to affect property sales (e.g., Michael et al., 2000; Walsh and Milon, 2016). Water clarity is measured by lowering a Secchi disc, which has alternating black and white quadrants, into the water. The depth at which the disc disappears is the Secchi depth (in meters), with a decrease in Secchi depth corresponds to a reduction in water clarity. We calculated Secchi depth from GLM model outputs as 1.7 divided by the light extinction coefficient (GLM output variable “extc_coef”). Surface (1 m depth) chl-a concentrations (μg L^{-1}) were based on the GLM output variable “PHY_TCHLA”. An increase in chl-a concentration corresponds to an increase in phytoplankton biomass and the appearance of surface scums, both of which are associated with reduced water quality. We focused on these output variables for summer months (June, July, August) when lake users are most likely to observe changes in water clarity due to phytoplankton blooms.

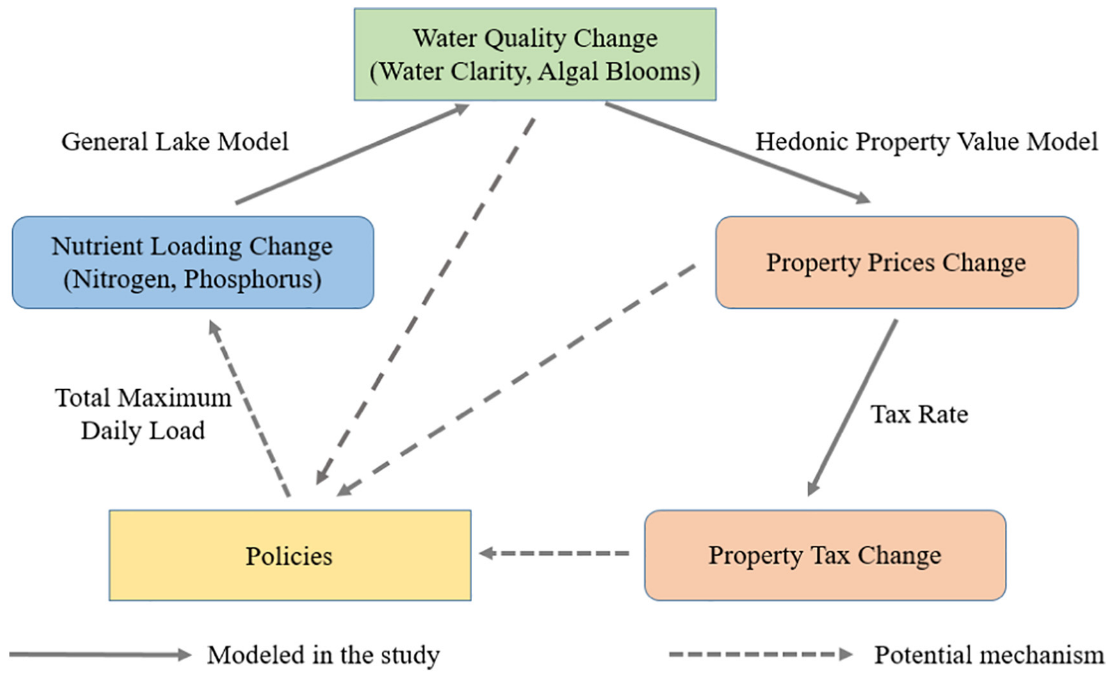

Fig. 2. Conceptual framework linking changes in nutrient loading to changes in property values and then into changes in property-tax revenues for a lake community. The effect of nutrient loading on water quality (as measured by water clarity and phytoplankton blooms) is simulated using GLM. Observed variation in lake water quality is used to estimate the effects on sale prices of properties near the lake, the hedonic model. Changes in the sale price of properties, in turn, affect property tax revenues used to fund local services such as public schools. Changes in nutrient loads are inputs to GLM to simulate changes in lake water quality. The GLM outputs are used as inputs to the estimated hedonic model to compute changes in property values and the resulting impacts on property-tax revenues.

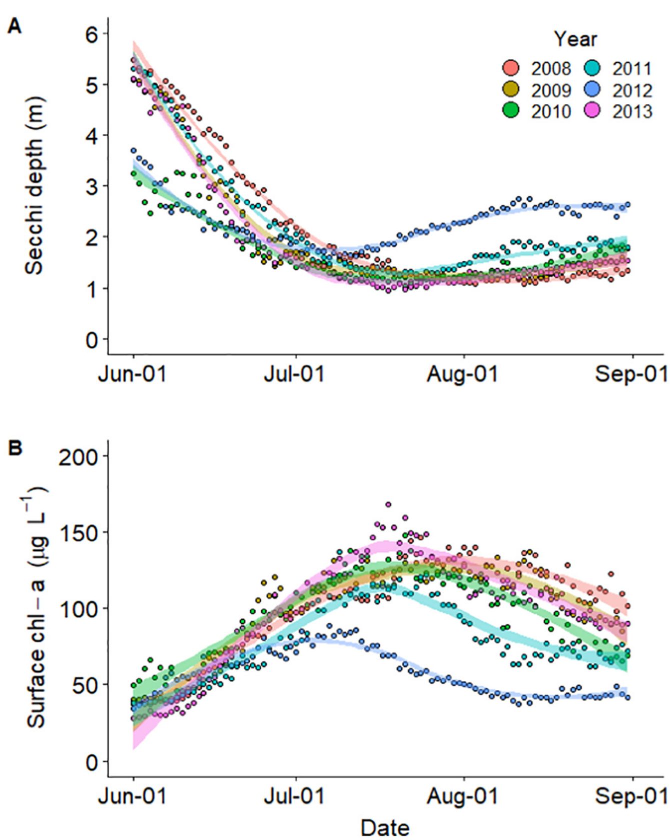

Fig. 3. Baseline GLM model output for summer (Jun. 1–Aug. 31) (A) Secchi depth and (B) surface (1 m) chlorophyll-*a* concentrations. Colors indicate the year.

We saved outputs for Secchi depth and chl-a concentrations at a daily timestep for 2008–2013, as these years overlapped with available data for the hedonic model (see Section 2.2). Daily estimates of summer (June, July, August) Secchi depth and surface chl-a concentrations in the baseline model were strongly correlated (Spearman's rho = -0.95; $p < 0.0001$). The baseline model captured seasonal variability in summer (June, July, August) Secchi depth, with minimum Secchi depths typically occurring in late July (Fig. 3A). The baseline model also captured inter-annual variability in Secchi depth and chl-a due to meteorological and inflow drivers. For example, within the model period, 2012 had the highest mean annual air temperature and the lowest total annual precipitation, and had correspondingly high summer Secchi depth and low summer chl-a concentrations compared to other model years. Across the full model period, mean ($\pm$ 1 standard error) summer Secchi depth was 2.04 $\pm$ 0.04 m, though daily summer Secchi depths ranged from 0.94 (Jul. 2013) to 5.47 m (Jun. 2008). Chl-a concentrations were generally lowest in early June, with a peak in late July, corresponding with minimum Secchi depth measurements (Fig. 3B). Across model years, mean summer chl-a was 88.3 $\pm$ 1.4 µg L^{-1}, with maximum and minimum daily concentrations of 167.7 (Jul. 2013) and 27.9 µg L^{-1} (Jun. 2013).

2.2. *Hedonic Model*

To capture the relationship between property sale prices and lake water quality as indicated by Secchi depth and chl-a concentrations, we estimated the hedonic model using observed water quality data. This approach is often used to estimate values for ecosystem services that affect market prices for properties, such as proximity to open space, urban tree cover, water quality, and other environmental amenities (Braden et al., 2011; Simons and Saginor, 2010; Taylor, 2017).

2.2.1. *Hedonic Model Specification*

We specified the hedonic model regression model as:

$$\ln(P_{it}) = \beta_0 + \beta_1 Lakefront_i + \beta_2 Distancetolake_i + \beta_{3w} Lakefront_i * lnWaterQuality_{tw} + \beta_4 S_i + \beta_5 L_i + \beta_6 T + \epsilon_{it} \quad (1)$$

where P_{it} is the sale price of property i in year t, $Lakefront_i$ is a binary variable for properties with frontage on the lake (1 for lakefront and 0 otherwise), $Distancetolake_i$ is a measure of the Euclidean distance from the centroid of a property to Lake Mendota; and $WaterQuality_{tw}$ is water quality in year t for measurement metric w (either Secchi depth or chl-a concentration). Because of the high degree of correlation between Secchi depth and chl-a concentration, separate equations are estimated for each of these water quality measures; the higher the concentration of chl-a, the lower the Secchi depth measure of water clarity. Lakefront properties are defined as properties abutting the shoreline of Lake Mendota and were identified using Google Earth. For lakefront properties, we set $Distancetolake_i$ equal to zero. We took the natural log of $WaterQuality_{tw}$ to reflect the fact that when water clarity (Secchi depth) is high, it becomes more difficult for property owners to recognize changes in water quality (Smeltzer and Heiskary, 1990). Similarly, when chl-a is small, it is likely property owners would find it difficult to observe small changes in surface phytoplankton concentrations. Property specific, time-invariant structural and lot characteristics (S_i) are variables typically used in hedonic model analyses, and include square feet of living area, lot acreage, house age, and number of bedrooms. Locational characteristics (L_i) include median income and demographic characteristics (e.g., race and age structure of population) at the Census block group level, and dummy variable fixed effects for school districts. We also included a variable in locational characteristics that indicates whether a property is closer to Lake Monona than to Lake Mendota (1 if closer to Monona and 0 otherwise). The βs are parameters to be estimated and ϵ_{it} is a random error term.

Our key variable for investigating the effect of water quality on property sales prices is the interaction term $Lakefront_i * lnWaterQuality_t$, which captures the effect of water quality on the sales prices of lakefront properties. We expected the estimate β_3 to be positive when Secchi depth is included in the model, which reflects increasing in property values as water clarity increases. We expected a negative relationship for chl-a concentration as a decrease in chl-a is associated with increasing property value. If β_{3j} is statistically significant for either Secchi depth or chl-a concentration, this indicates that lake water quality affects sale prices of lakefront properties.

We use Secchi because it is a summative measure that can be observed by buyers and sellers, while chl-a is a measure of water quality of direct interest to limnologists. Secchi depth readings are an indicator of all particles in the water column, including chl-a, sediments, and other particulate matter, that affect the clarity of lake water. Chl-a is one component of the water column and is an indicator of phytoplankton biomass. Thus, β_{3w} is expected to be larger in absolute value in the Secchi equation relative to the chl-a equation. That is, a one-unit change in chl-a will affect Secchi measurements but does not reflect all elements in the water column that affect water clarity.

Contemporary hedonic models often use a quasi-experimental design to control for unobserved variables that might be correlated with the policy variable of interest, lake water quality here. Due to the limited number of observations in the study area, we follow Kuminoff et al. (2010) using time fixed effects (T – dummy variables for the year of each property sale and the month when the sale occurred) to control for omitted variables that vary over time and are potentially correlated with temporal changes in water quality.

2.2.2 Hedonic Model Data.

We used observed water quality (Secchi depth, chl-a concentration) data from the NTL-LTER to estimate the hedonic model (Fig. 4). The NTL-LTER water quality data were collected at the deepest part of the lake, which is considered to be the most representative sampling location within the lake. It is also the location that GLM simulates as representative of whole-lake water quality. Secchi depths were measured fortnightly and surface chl-a concentrations were measured every 30 days during summer months. A change in NTL-LTER chl-a instrumentation created an uncorrectable bias in concentrations measured between 2002 and 2007. To address this discrepancy, we used observed Secchi depth and chl-a data from 2008 through 2015 only to estimate the hedonic model.

A fundamental assumption of hedonic models is that buyers and sellers are fully informed regarding property characteristics. The empirical investigator, without buyer-specific data, does not know what information on lake water quality buyers use when contemplating purchases of properties. We use summer mean water quality values to represent informed buyers perceptions of water quality in the hedonic model for both Secchi depth and surface chl-a concentrations (Michael et al., 2000).

If a sale happened in the first half of the year, January 1st to June 30th, we used the summer water quality measurements from the prior year in the hedonic model because buyers cannot observe water quality when Lake Mendota is frozen during the winter months. If the sale happened in the second half of the year, July 1st to December 31st, we use summer water quality from the same year in the hedonic model.

We obtained property transactions data for Dane County, WI from two sources (National Association of Realtors and CoreLogic). These data include property sale prices and selected property characteristics. We include arms-length transactions of single-family residential properties, which are sales between willing sellers and willing buyers, for estimation. We exclude from the analysis properties with extreme sales prices (i.e. any observation with price per square foot less than \$20 or greater than \$500 per square foot). The final dataset contained 13,169 property-sale records (Fig. 5).

To account for the Great Recession and associated changes in residential-property markets, we used transactions from 2009 to 2015 (Dominguez and Shapiro, 2013). We adjusted sales prices to 2015 dollars using the Consumer Price Index for all urban consumers to reflect inflation. Year and month fixed effects were included in the estimation to capture adjustments in the residential property market as the economy progressed beyond the Great Recession. These fixed effects also are crucial for identifying the water quality effect as the estimation includes a single water quality measure for each year.

We geocoded each transaction in the data using GIS to identify Mendota lakefront properties, distance to Lake Mendota, and the relative proximity of the home to Lake Mendota versus Lake Monona. To identify a property's proximity to the lakes, we merged the property sales data with lake boundaries from the USGS National Hydrography Dataset. We also merged the property sales data with census block group data from the U.S. Census Bureau to obtain community demographic data. We overlaid property sales, lake, census and school district data layers to compile the dataset used to estimate the hedonic model. In general, lakefront properties are larger, somewhat older, and more expensive than non-lakefront properties (Table 1).

2.2.2. Hedonic Model Estimation Results

The estimated coefficient on the *Lakefront* variable is significant in both the Secchi and chl-a equations specifications, indicating a significant price premium for properties located along the shoreline of Lake Mendota (Table 2). The estimated *Distancetolake* coefficients are negative and significant, indicating that the property values decrease with distance from the lake. The coefficients on the distance variables should be interpreted with caution as distance to the lake is correlated with distance to the state capital building, the Madison central business district and the University of Wisconsin campus. The campus is located on the shore of Lake Mendota and the state capital and central business district are located about a half mile from campus.

Other property characteristics such as square footage of living area, house age, number of bathrooms, median household income, age and race are statistically significant in explaining variation in property sale

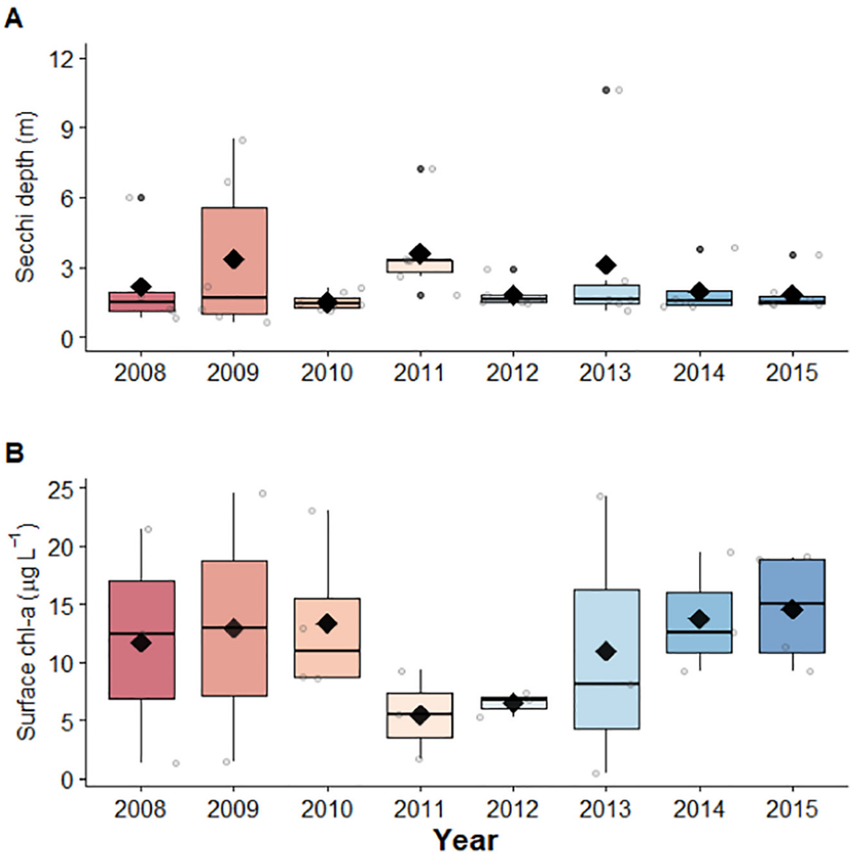

Fig. 4. Observed water quality data for summer (Jun. 1–Aug. 31) across modeled years in hedonic model (2008–2015). Boxes represent the first quartile, median, and third quartiles of the distribution of measured water quality data (gray points) for each modeled year (2008–2015); whiskers represent 1.5× the interquartile range. Black diamonds indicate the mean value for each year.

prices. Appendix Table A8 reports school district and year and month of property sale fixed effect coefficient estimates.

The primary variables for the coupling analysis are *Lakefront*ln (Secchi)* and *Lakefront*ln(chl-a)*. Both interaction terms are significant and have the expected signs, which were positive for Secchi and negative for chl-a. As discussed above, we expected that the coefficient on the Secchi interaction variable would be larger than for the chl-a interaction variable in absolute value. This expected relationship is borne out by the estimation results.

An interesting outcome is that the coefficient on *Lakefront* is larger in the chl-a equation than in the Secchi equation. This suggests that the unobserved changes in water quality captured by Secchi measurements, but not by chl-a measurements, are captured by the *Lakefront* coefficient in the chl-a equation.

Finally, we did try estimating hedonic models where the water quality variables were interacted with distance of each property from the lake to see if the effect of water quality on property values extended spatially through the community, but these variables were not statistically significant. Thus, the only broader community impacts in the current analysis will arise through changes in property-tax revenues from lakefront properties.

2.3. Coupling the GLM With the Hedonic Model (Nutrient Loading Scenarios)

We link the GLM and hedonic model results presented in the previous two sections to create a coupled limnological-economic (natural-human) modeling tool that allows us to connect changes in nutrient loading with changes in water quality and ultimately, to changes in property values in communities surrounding the lake. To model these connections, we first use GLM to simulate changes in water quality during the summer months in response to nutrient loading scenarios. We then use GLM predictions of changes in Secchi depth and chl-a concentrations and the estimated coefficients of the hedonic model to predict changes in property values in the lake catchment.

We ran the calibrated GLM for eight scenarios of changes in N and P loading (j = ± 25, 50, 75 and 100%) to Lake Mendota. We chose these scenarios to cover a wide range of potential changes in nutrient loading that will provide reference bounds to inform potential policy actions. The scenarios are based on changes in N and P concentrations flowing into the lake relative to observed N and P inflow concentrations during the 13.5-year model period. For each scenario, we changed inflow concentrations in the GLM input file of all N and P fractions simultaneously and by the same proportion. This is a simplifying assumption that is consistent with a change in the use of purchased fertilizers by farmers, which contain fixed proportions of N and P (Maguire et al., 2009). We ran GLM for each of these scenarios to simulate changes in Secchi depth and chl-a concentrations.

Using simulated changes in these water quality metrics from GLM, we then used the estimated parameters from the hedonic model to predict changes in property values. Letting s_j denote the nutrient loading scenarios, we predicted the sale prices of lakefront properties as:

$$\widehat{P}_{s_j} = \exp\left(\widehat{\beta}_0 + \widehat{\beta}_3 (Lakefront_i = 1) * ln\,\widehat{WaterQuality}_{s_j} + \widehat{\beta}\overline{X}\right) \tag{2}$$

where $\widehat{P}_{s_j}$ is the predicted sale price for water quality scenario s_j, the $\widehat{\beta}\,s$ are estimated coefficients and $\overline{X}$ is a vector of the means of other explanatory variables multiplied by their respective estimated coefficients ($\widehat{\beta}$). The $\widehat{WaterQuality}_{s_j}$ is the predicted water quality level associated with each nutrient loading scenario. The predicted sales price on the left-hand side of Eq. (2) is the capitalized value of the stream of benefits a property owner enjoys from the property at the specific level of water quality.

To obtain changes in property values we derived the proportional changes in water quality as:

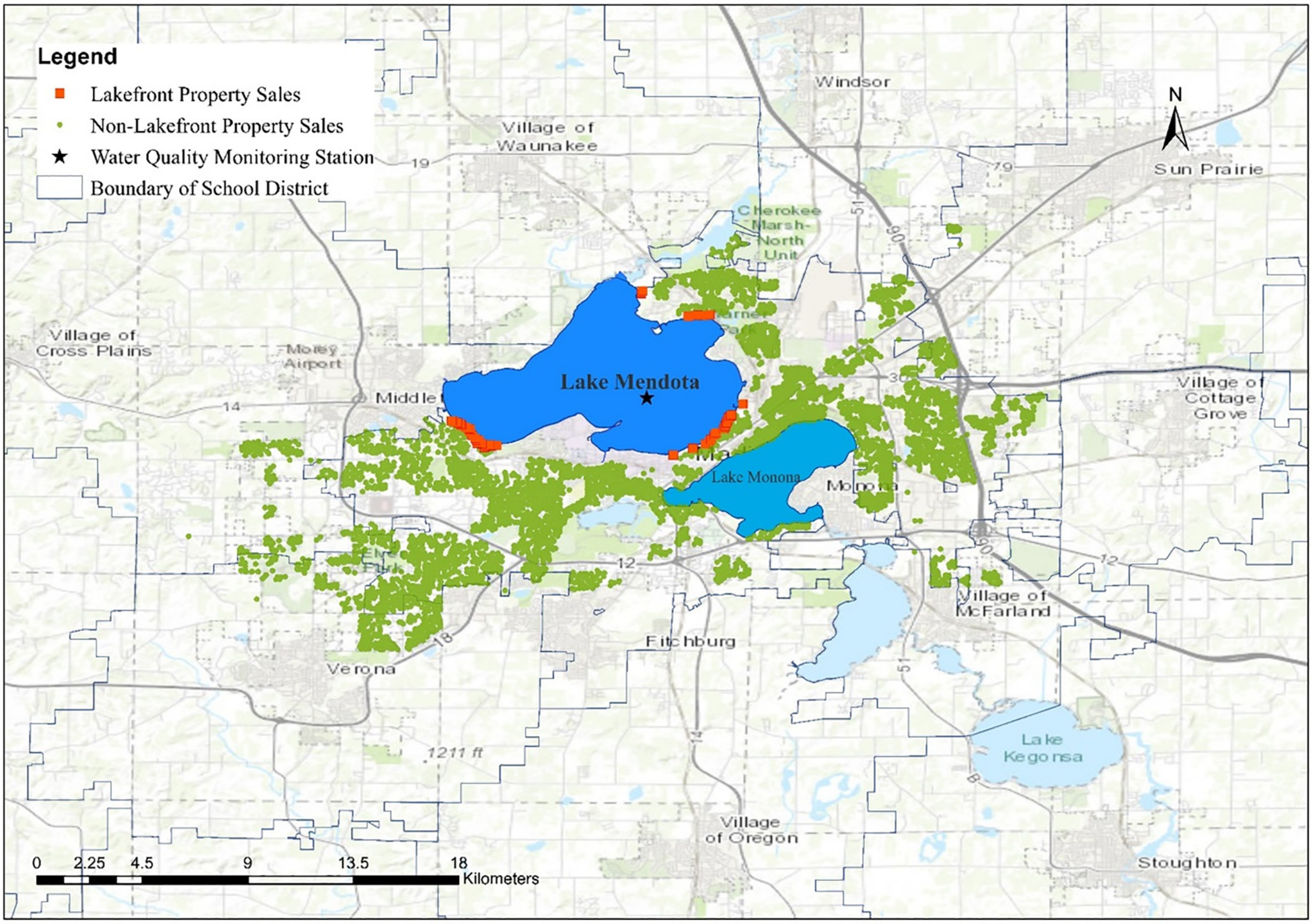

Fig. 5. Geographical location of property sales of the estimation period (2009–2015). Red dots represent lakefront property sales (n = 100), green dots represent non-lakefront property sales (n = 13,069). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\Delta_{pr}\widehat{WQ}_{sj} = \frac{\widehat{WQ}_{sj}}{\widehat{WQ}_{sb}} \tag{3}$$

where s_b is predicted baseline water quality and s_j is the predicted water quality under each nutrient loading scenario. Building on Eq. (3), the proportional change in property values is:

$$\Delta_{pr}\widehat{P}_{sj} = e^{\widehat{\beta}_3 \ln(\Delta\widehat{WQ}_{sj})} \tag{4}$$

Building on Eq. (4), the capitalized change in property value for the property with the average sales price ($\overline{P}$) in the data is:

$$\Delta\widehat{P}_{sj} = (1 \pm \Delta_{pr}\widehat{P}_{sj}) * \overline{P} \tag{5}$$

We aggregated changes in property values ($\Delta\widehat{P}_{sj}$) for each scenario to all lakefront properties as: $agg\widehat{P}_{sj} = \Delta\widehat{P}_{sj} * k$, where k is the total number of lakefront properties (those that sold and did not sell during the study period).

While the estimated hedonic model only includes the effect of water quality on lakefront properties, changes in the value of these properties can have financial implications for the entire community via changes in property tax revenues. Using number of lakefront properties in each of the five communities with frontage on Lake Mendota (c = Madison, Maple Bluff, Middleton, Shorewood Hills, Westport), we compute the weighted property tax mill rate m as: $m = \sum_{c=1}^{5} \frac{k_c m_c}{k}$, where k_c and m_c are community-specific mill rates and number of lakefront properties.

We multiplied the capitalized aggregate change in property values by the weighted property tax mill rate to predict the potential gains or losses in property tax revenues ($\widehat{PTR}$) due to a change in water quality:

$$\Delta\widehat{PTR}_{c,sj} = \left(\frac{\Delta\widehat{P}_{c,sj}}{1{,}000}\right) * k * m. \tag{6}$$

Property tax mill rates are levied per \$1000 of the assessed property value so $\Delta\widehat{P}_{c,sj}$ is divided by 1000. We used predicted changes in property values as proxies for assessed value changes. As communities reassess properties over time, the change in capitalized value due to changes in water quality will be reflected in updated assessments.

Our coupling differs, yet complements, the coupling presented by Liu et al. (2019). The Liu study uses a general hydrologic model (SWAT) that is not specific to lake ecosystems (Francesconi et al., 2016), while we employ GLM that is specific to lake systems. This paper also explains more about GLM than Liu does about SWAT but, at the same time, SWAT is a more well-known model in the literature; GLM is best known currently in the limnology literature where it was developed. The Liu study investigated a watershed that contained a reservoir, while our study focused on a natural lake and nutrient loads from the catchment into the lake. Liu used SWAT predictions as input to estimate the hedonic model, while in the current study we use observed water quality data. Comparing the estimation of hedonic models with simulated versus observed data is an interesting auxiliary area of investigation for future research. In the current paper, we use GLM to predict changes in water quality as inputs to the estimated hedonic model to compute effects on property values from different nutrients loads to the lake, while the Liu study did not appear to do such model linking. Thus, the similarities and differences of these papers collectively push the frontier of coupled natural-human model linking in the context of lake

Table 1
Summary statistics for residential property sales: 2009–2015.

Variable	Unit	Lakefront (N = 100)		Non-lakefront (N = 13,069)	
		Mean	Standard deviation	Mean	Standard deviation
Property characteristics					
Sales price	2015 US$	$569,921	$353,741	$222,957	$112,461
Log of sales price	2015 US$	13.1	0.6	12.2	0.4
Living area	square feet	2722	1288	1899	798
Lot size	acres	0.30	0.20	0.21	0.15
House age	years	32	17	28	16
Number of bathrooms	count	3	1	2	1
Neighborhood and locational characteristics					
Distancetolake	Meters	0	0	4231	2640
Lake Monona dummy	1 if Monona closest	0	0	0.378	0.485
Median household income	2015 US$	$54,771	$10,536	$64,962	$22,409
Population > 65	%	10.2	4.6	10.7	6.0
African American	%	5.4	2.2	6.4	6.4
Distribution of school districts					
Sales in District 5503180.	%	0	–	0.92	–
Sales in District 5508520	%.	100	–	82	–
Sales in District 5508910	%	0	–	0.46	–
Sales in District 5509510.	%	0	–	4.18	–
Sales in District 5509810.	%	0	–	0.02	–
Sales in District 5514640.	%	0	–	2.06	–
Sales in District 5515330	%	0	–	10.36	–
Distribution of sales by year					
Sales in 2009	%	11	–	13	–
Sales in 2010	%	8	–	11	–
Sales in 2011	%	19	–	11	–
Sales in 2012	%	17	–	15	–
Sales in 2013	%	14	–	17	–
Sales in 2014	%	14	–	15	–
Sales in 2015	%	17	–	18	–
Distribution of sales by month					
Sales in January	%	6	–	4	–
Sales in February	%	1	–	5	–
Sales in March	%	4	–	7	–
Sales in April	%	6	–	9	–
Sales in May	%	8	–	12	–
Sales in June	%	13	–	15	–
Sales in July	%	12	–	14	–
Sales in August	%	13	–	10	–
Sales in September	%	8	–	7	–
Sales in October	%	6	–	7	–
Sales in November	%	12	–	6	–
Sales in December	%	11	–	4	–

Note: We assume the Distancetolake for all lakefront properties is 0.

ecosystems.

3. Simulation Results and Scenario Evaluations

In this section, we report the modeled results of nutrient loading scenarios in terms of water quality impacts and the resulting consequences for property prices and property taxes.

3.1. Water Quality Simulation Results

For both Secchi depth and chl-a concentrations, changes were not symmetric across the nutrient loading scenarios. We observed greater proportional changes under a reduction in nutrient loading than under an equivalent increase in nutrient loading (Fig. 6). The most extreme reduction in nutrient loading (100% decrease) resulted in a mean summer Secchi depth of 7.15 ± 0.02 m, which is a 250% increase relative to the baseline (Fig. 6A). At the other extreme, a 100% increase in nutrient loading resulted in a mean summer Secchi depth of 1.80 ± 0.04 m, which is approximately a 12% decrease relative to the baseline. For chl-a, a 100% reduction in nutrient loading resulted in mean summer concentrations of 4.19 ± 0.11 μg L^{-1}, which is a 95% decrease relative to baseline (Fig. 6B). A 100% increase in nutrient loading resulted in mean summer concentrations of 103.0 ± 1.4 μg L^{-1}, which is a 17% increase relative to baseline. In a lake with high nutrient concentrations and poor water quality, these results suggest that relatively little additional degradation in these metrics of water quality occurs with further increases in nutrient loading. In contrast, relatively greater gains in water quality may be obtained with an equivalent proportional decrease in nutrient loading.

3.2. Property Value and Property Tax Effects

A one-meter increase in mean summer Secchi depth leads, on average, to an $11,412 increase in property price, and a 1 μg L^{-1} decrease in the mean summer surface concentration of chl-a leads, on average, to a $1263 increase in property price. Based on the average sale price of $569,921 for properties with frontage on Lake Mendota, these represent changes of 2% and 0.2%. The respective aggregate changes in property values across all lakefront properties are $9,243,720 for a one-meter increase in Secchi depth and $1,023,030 for

Table 2
Hedonic property-value model estimation results using mean water quality measurements.

Variable	Secchi depth	Chl-a concentration
Lakefront dummy	0.353***	0.598***
	(0.008)	(0.015)
Distancetolake	−0.00005***	−0.00005***
	(3.02e-06)	(3.02e-06)
Lakefront*ln(Secchi)	0.129***[a]	
	(0.003)	
Lakefront*ln(Chl-a)		−0.057***
		(0.004)
Lake Monona dummy	0.004	0.004
	(0.013)	(0.013)
Living area	0.0004***	0.0004***
	(0.00003)	(0.00003)
Living area^2	−2.38e-08***	−2.39e-08***
	(4.52e-09)	(4.53e-09)
Lot size	0.008	0.009
	(0.067)	(0.067)
Lot size^2	0.013	0.013
	(0.017)	(0.017)
House age	−0.003***	−0.0027***
	(0.0006)	(0.0006)
House age^2	−7.15e-06	−7.43e-06
	(7.81e-06)	(7.81e-06)
Number of bathrooms	0.027***	0.027***
	(0.005)	(0.005)
Median household income	4.24e-06***	4.24e-06***
	(4.14e-07)	(4.14e-07)
% of population > 65	−0.008***	−0.008***
	(0.002)	(0.002)
% of African American	−0.014***	−0.014***
	(0.0007)	(0.0007)
Constant	11.654***	11.65***
	(0.032)	(0.033)
School district fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Observations	13,169	13,169
R-squared	0.602	0.602

Notes: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors have been clustered at the school district level. Detailed coefficient estimates of fixed effects are reported in supporting material table A8.

a one-meter decrease in chl-a concentration.

In the context of our scenarios, a 25% increase in nutrient loading will, on average, lead to a loss of \$2883 to \$5756 for a lakefront property, depending on whether we look at chl-a concentrations or Secchi depth, respectively (Table 3). These changes are equivalent to 0.5% to 1.0% of the average lakefront property sales prices. On the other hand, if we consider a 25% decrease in nutrient loading, lakefront property owners gain \$3994 to \$6897 per property on average, which is equivalent to a slightly larger increase of 0.7% to 1.2% of the average property sale price. The disparity between property values for nutrient increases and decreases becomes starker as the magnitude of the nutrient loading changes, e.g., 17.6% for a 100% decrease and 1.6% for a 100% decrease based on Secchi depth.

The reader will note that the changes in property values based on Secchi measurements are larger than the comparable changes in values based on chl-a concentrations. This difference is not surprising as chl-a concentration is one component of the water column that affects clarity, but not the only component. Thus, while chl-a is a measurement of fundamental importance to a limnologist, Secchi disks provide a summative measure of what a layperson sees when they look into a lake.

At the community scale, considering all lakefront properties in the five municipalities with frontage on Lake Mendota, improved water quality arising from 25% and 100% reductions in nutrient loading yield increases in annual tax revenues ranging from about \$73 thousand to nearly \$2 million (Table 4). The \$1,984,356 increase in tax revenues (2015\$) from a 100% decrease in nutrient loading, based on chl-a, is about 0.3% of the 2014 annual property tax revenues in the five municipalities. While this is a small percentage, taking the average Wisconsin teacher salary of \$51,469 in 2017–18 (Will, 2019) and assuming a fringe benefit rate of 36%, \$2 million in annual property tax revenue could fund 28.6 teaching positions.

Our results suggest that a decrease in nutrient loading will generate greater economic benefits than the loss associated with an equal proportionate increase in nutrient loading. The asymmetry in the effects of increases and decreases in nutrient loading on water quality (see Fig. 6) drives the asymmetry in property sale price effects and subsequent changes in property-tax revenues. This occurs because Lake Mendota is eutrophic and has high N and P concentrations due to a long history of nutrient loading. Thus, decreases in nutrient loads result in larger improvements in water quality than proportionately similar increases in nutrient loads reduce water quality. Further, a small decrease in nutrient loading (25%) has a much smaller impact than a large decrease (100%). Because of the high N and P concentrations in the lake, it is necessary to have a substantial reduction in nutrient loading to substantially improve water quality.

The greater the nutrient loading restrictions, the more pronounced property value effects are likely to be and the ripple effects of changes in property tax revenues through the community to those who do not own lakefront property. While 100% changes in nutrient loads to the lake may be unlikely and if such changes occurred, the property market would be expected to adjust, the 25% and 100% change scenarios might be expected to show the outer bounds of the economic effects in terms of the effects on property values and property taxes.

4. Conclusions and Discussion

The scope of the U.S. Clean Water Act underscores the need to examine the potential benefits and costs of changes in nutrient loading (Cropper and Isaac, 2011), motivating analyses that examine the connectivity between freshwater systems and human actions (Cobourn et al., 2018). To date, the literature coupling limnological simulation models with models of economic consequences of changes in water quality is sparse. By coupling models of lake water quality and property prices, our study is an example of coupled modeling to provide evidence-based, integrated assessment analyses of policies that address nutrient pollution.

Our GLM results indicate that in Lake Mendota, increases in nutrient loads have little effect on water quality as measured by Secchi depth and surface chl-a concentration. This result is due to high nutrient concentrations in the lake. Conversely, reductions in nutrient loading can lead to substantial improvements in water quality. One might expect the opposite pattern for an oligotrophic lakes with low nutrient concentrations, in which reductions in nutrient loading might do little to improve water quality while increases in nutrient loading could result in proportionally larger reductions in water quality.

It follows that the greatest capitalized changes in property values for Lake Mendota are for reductions in nutrient loading. There are smaller changes in property values for increases in nutrient loading. Thus, the costs and benefits associated with different policies depend critically on the starting point for the lake water quality and the direction of the policy change being evaluated. This suggests that the importance of policies to protect lakes with high water quality from nutrient loading and the benefits of reducing nutrient loading in lakes with low water quality.

Future studies might consider including the coupling of a recreation demand model that would extend the economic effects to residents of the community that do not own lakefront property but uses the lake for recreation (e.g., Zhang and Sohngen, 2018). In fact, some who do not use the lake for recreation in the current state might choose to recreate on the lake if water quality improved. Even people who do not use a lake for recreation might benefit from improvements in water quality if

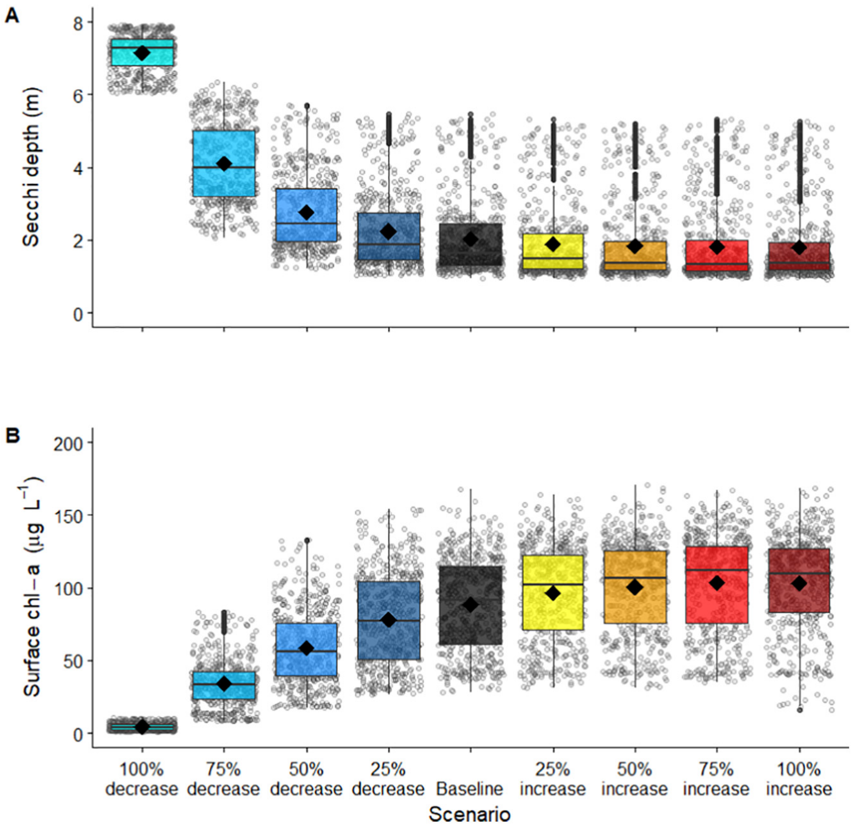

Fig. 6. GLM model outputs for summer (Jun. 1–Aug. 31) across modeled years (2008–2013). A) Secchi depth and (B) surface chlorophyll-a concentrations under different nutrient loading scenarios relative to the baseline, ranging from a 100% decrease in inflow nitrogen and phosphorus to a 100% increase relative to baseline concentrations. Boxes represent the first quartile, median, and third quartiles of the distribution of daily values (gray points) for each scenario across modeled years (2008–2013); whiskers represent 1.5× the interquartile range. Black diamonds indicate the mean value for each scenario.

Table 3
Changes in the mean value for lakefront properties.

Nutrient load change scenarios	Change in property values	
	Secchi depth changes	Chl-a concentration changes
25% increase	−$5756 (−1.0%)	−$2883 (−0.5%)
50% increase	−$7808 (−1.4%)	−$4162 (−0.7%)
75% increase	−$8587 (−1.5%)	−$5007 (−0.9%)
100% increase	−$9146 (−1.6%)	−$4995 (−0.9%)
25% decrease	+$6897 (1.2%)	+$3994 (0.7%)
50% decrease	+$23,135 (4.1%)	+$13,531 (2.3%)
75% decrease	+$53,659 (9.4%)	+$31,854 (5.6%)
100% decrease	+$100,190 (17.6%)	+$108,161 (19.0%)

Notes: Values in parentheses represent corresponding percentage changes in property values for each scenario based on the average selling price of lakefront properties during the study period of $569,921.

Table 4
Changes in annual property tax revenues for lakefront communities.

Nutrient load change scenarios	Annual tax revenue change	
	Secchi depth changes	Chl-a concentration changes
25% increase	−$105,601	−$52,892
50% increase	−$143,248	−$76,357
75% increase	−$157,540	−$91,860
100% increase	−$167,795	−$91,640
25% decrease	+$126,535	+$73,275
50% decrease	+$424,442	+$248,244
75% decrease	+$984,445	+$584,404
100% decrease	+$1,838,118	+$1,984,356

Notes: Computation based on number of lakefront properties (n = 810) and weighted average property tax mill rate ($/1000) across five lakefront communities (m = 22.65).

they hold non-use values for the lake as part of their community culture (e.g., Loomis, 2006).

On a more granular level, our results could be used in public education efforts to motivate property owners to take actions that improve water quality and thereby their property values. That is, property owners might be receptive to educational programs on actions they can take on their own property from which they will benefit directly. Potential increases in lakefront property prices can motivate property owners to take direct actions such as reducing fertilizer usage on lawns and planting riparian buffers along the lakeshore. These motivations can help to unite property owners, scientists, environmental activists and public decision makers to use coupled models to support evidence-based policy discussions and actions.

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Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://

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