Reeling in the Damages: Harmful Algal Blooms' Impact on Lake Erie's Recreational Fishing Industry

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Abstract

Lake Erie is one of the most valuable natural resources in the United States, providing billions of dollars in benefits each year to recreationalists, homeowners and local governments. The ecosystem services provided by Lake Erie, however, are currently under threat due to more intensive and frequent harmful algal blooms. This paper provides recreational damage estimates caused using spatially and temporally varying algae and annual fishing permit sales data collected between 2011 and 2014. Results indicate that annual fishing license sales drop between 5% and 11% when algal conditions surpass the World Health's Organization's moderate health risk advisory threshold of 20,000 cyanobacteria cells/mL. For Lake Erie adjacent counties experiencing a large, summer-long algal bloom, this would result in approximately 3,600 fewer fishing licenses issued during that time and approximately $2,225,000 to $5,575,000 in lost fishing expenditures. There appears to be no additional drop in fishing permit sales after algal conditions surpass this threshold however, suggesting that policies aimed at eliminating, rather than constraining, algal concentration levels are more beneficial to the Ohio angling industry.

Keywords: harmful algal bloom; count data; recreation; revealed preference; cyanobacteria; Lake Erie

JEL: Q25, Q51, Q53, Q57

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Highlights

- Estimate the effect of crossing WHO cyanobacteria threshold on fishing permit sales
- 14% reduction in permit sales for near lake zip codes experiencing an algal bloom
- Extent of HAB related losses limited to zip codes within 20 km of Lake Erie
- $5,575,000 in lost fishing expenditures associated with a summer-long bloom

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1. Introduction

Lake Erie provides $10.7 Billion in tourism benefits per year with a $2 Billion sports fishery (Great Lakes Commission 2014). However, this large flow of benefits is under threat from a variety of sources including: Zebra Mussels, Asian Carp invasion, and more recently, increasing annual blooms of harmful cyanobacteria. Harmful algal blooms (HABs) impair water quality and often lead to public health warnings to either avoid drinking, swimming and in severe cases any contact with the water. In addition, it is predicted that the incidence of these blooms is likely to increase in duration and extent as a result of climate change and increased nutrient runoff which provide the needed resources for the bacteria causing blooms (Robson and Hamilton 2003; Mooij et al. 2005).

Cyanobacteria, often referred to as blue-green algae, are the most common form of harmful algal blooms (HABs) associated with Lake Erie and freshwater lakes across the Midwest. These HABs can spread rapidly in the summer months in the presence of sunlight and warm, still waters, producing the harmful toxin *microsystin* (Carmichael 1992). One of the more damaging blooms in recent memory occurred in 2014 when 500,000 residents in Toledo, OH were warned to not drink their tap water due to the concentrations of such toxins, subsequently leading to at least 60 hospitalizations. These blooms can last three to four month in duration (such as in 2011) and often occur in the summer and autumn months, covering large areas of the lake. While blooms are often associated with drinking water and adverse health impacts, ingestion is not the only means through which individuals can be harmed by these toxins.

In addition to drinking water concerns, state and local authorities are increasingly forced to issue recreational public health advisories, warning to avoid all contact with the water and providing a serious impediment to the success of local angling economies. In other cases, excess algal blooms prevent sunlight from reaching the bottom of the water column and over time can lead to aquatic life dependent on this sunlight to diminish, significantly impacting the ecosystem and harming the native gamefish populations. Whether through an explicit warning to stay away from the water or through the perceived impact on the likely catch-rate, the presence of cyanobacteria are likely to have a significant negative impact on the angling industry.

This paper uses a unique dataset of all fishing license sales for Lake Erie bordering counties in Ohio to quantify the potential adverse effect on anglers when harmful algal blooms occur. We use monthly sales data on purchases of annual fishing licenses to estimate a negative binomial count data model of fishing license sales at the zip code level. To our knowledge, this is the first revealed preference analysis of the effects of HABs on recreational anglers in the Great Lakes. Following prior literature suggesting a limited spatial extent of algal impacts, we limit our focus to 8 counties that border Lake Erie (Jørgensen et al. 2013). Results from our preferred specification suggest a robust and sizeable decrease in license sales of approximately 11% for locations and months experiencing algal blooms. Back of the envelope cost analysis subsequently reveals a total decrease of economic activity associated with angling in the state of Ohio of roughly $2,225,000 to $5,575,000 when average algal conditions are above the WHO's moderate advisory threshold for an entire summer.

The remainder of the paper is structured as follows. The next section briefly reviews the literature on water quality and recreation behavior. This section is followed by a discussion of the fishing license and HAB data necessary for analysis before presenting a negative binomial estimator of fishing license counts in section four. Section five contains the main estimation results and section six concludes with a discussion of potential impacts to the angling industry due to increased algal bloom duration and frequency.

2. Water Quality and Economic Behavior

Linking water quality changes to residential and recreational decisions has long been a focus of applied researchers (Smyth et al. 2009; Vesterinen et al. 2010; Kosenius 2010). A number of ecological and behavioral factors are known to influence water quality conditions; however eutrophication is often given special consideration due to its strong ties with human behavior. A standardized measure of the eutrophication process has not been established within the literature leading many to use measures such as suspended solids and dissolved nitrogen (Poor et al. 2007), lake depth (Bejranonda, et al. 1999), fecal coliform (Leggett and Bockstael 2000), and pH levels (Tuttle and Heintzelman 2015). Despite this wide range, causal relationships between water quality and economic variables of interest are generally robust.

The prevalence of publicly available housing transactions data across the country coupled with the relative difficulty of obtaining revealed preference data on recreation, often through survey work, has led to an extensive literature examining water quality changes using hedonic property value models (see, e.g. Boyle et al. 1999; Walsh et al. 2011). In general these studies find a strong, positive relationship between water quality improvements and nearby property values across a wide range of data, research designs and empirical strategies used to reveal this relationship. While recreational studies generally find a similar positive impact of improved water quality, the effect can occur through various channels, including swimming, boating, and/or angling.

Research most closely related to our study has considered the recreational impact of algal blooms in New Zealand using choice experiments. Anglers in New Zealand were estimated to have aggregate damages of 10.5 Million NZ$ caused by the spread of the invasive, nontoxic algae, Didymosphenia Geminate (Beville, et al. 2012). Additional studies focusing on the Black and Baltic Seas found a willingness to pay in Bulgaria of 0.27% of annual income to eliminate algal blooms in a nearby bay (Taylor and Longo 2010). A contingent valuation study of the Baltic Sea drainage basin estimated that a reduction in eutrophication through a 50% reduction in nutrient loading would be valued at $3.4 Billion USD per year across the basin, although this value takes into account much more than the recreational benefits accrued from this reduction (Gren et al. 1997).

In a U.S. context, extensive survey work has been carried out to elicit respondents' preferences for water quality. A study in Iowa found that, ceteris paribus, higher concentrations of cyanobacteria in a lake would decrease the likelihood of visitation (Egan et al. 2009). A recent survey of Ohio anglers found that 96% of respondents were aware of HABs and that half of the respondents had in some way altered their behavior in response to such blooms. Participants, for example, stated they often responded to HABs by either choosing a new recreation location or completely forgoing angling activity (Sohngen et al. 2015).

Information collected from Great Lake recreators has also been utilized in travel cost models to estimate welfare gains/losses attributed to water quality changes (Yeh et al. 2006). A one day reduction in advisory days along the Lake Erie shoreline, for example, is predicted to generate $28 in benefits per visitor during the summer season (Murray et al. 2001). At a more aggregate level, a one day beach closure along the Michigan shoreline is expected to cost, across all beach goers, between $130,000 and $24 Million depending on the location of the closure (Song et al. 2010). Welfare estimates across and within these studies vary significantly, however, due to the uncertainty surrounding the total affected population size.

We build on the existing water quality recreation research in several ways. First, we use a more direct measure of water quality, the actual level of toxin in the water (Cyanobacteria cells/mL), which drives advisories and health warnings. Second, we exploit heterogeneity across both space and time in our Lake Erie study area to examine the role of increasing levels of water quality degradation. Traditionally, the variation needed to examine this has resulted in researchers comparing across locations with potentially different unobservables, as one would expect when comparing outcomes across different lakes. The preferred specification within this study, however, is able to avoid a substantial source of potential bias by deriving damage estimates using temporal algal variation while absorbing time-constant unobservables through spatial controls.

3. Data

Annual fishing registration data for the 8 Ohio counties highlighted in Figure 1 was gathered from the Ohio Department of Natural Resources Fishing License and Permit Sales database (ODNR 2015). Zip codes have been overlaid as these provide the unit of count observation needed for our econometric specification. Annual license counts were assembled at the zip code by month unit between February 2011 and December 2014 using mailing address and date of sale information collected from this database.[2] Having assembled and aggregated permit count data, additional spatial measures were attached to each observation using GIS shapefiles collected from the US Census, the USGS's National Hydrography Dataset and the ODNR's Office of Coastal Management. In particular, proximity to Lake Erie and distance to the closest public access point where either boating or fishing is allowed were measured using ArcGIS.

In addition to license information, 10 day algal-composite data spanning 2009 - 2014 have been acquired from the National Oceanic and Atmospheric Administration (NOAA 2015) and Wynne and Stumpf (2015). Using remote sensing data, Wynne and Stumpf (2015) constructed 1100x1100 meter Cyanobacterial Index grid values for all of Lake Erie using remote sensing data. Lake Erie HAB raster images are available only for the summer and fall months (June – October) in part due to low or undetectable levels of algae present during much of the winter and spring. During the summer and fall months a significant degree of water quality heterogeneity exists within our sample. A snapshot of the spatial and temporal heterogeneity in HAB density is shown for two time periods (September 2011, 2012) in Figures 2 and 3.

Mean algal readings over time are shown in Figure 4 with moderate and high algal advisory thresholds plotted as dashed lines. Two observations are evident from this figure. First, there is substantial inter-annual heterogeneity with significant numbers of algal readings both above and below each algal threshold. Second, algal levels quickly trend towards zero outside of the available HAB data. As such, it seems reasonable to expect that this variation, coupled with the spatial variation shown in Figures 2 and 3, is likely influencing fishing and recreation behavior along Lake Erie. To the extent that anglers are likely substituting across space from a poor water quality location to a better location suggests that any potential findings of reduced angling sales will likely be an underestimate of the true impact on recreation behavior.

[2] Zip codes stretching across county boundaries were assigned to the county in which the majority of the population resided.

To form additional control variables, we assembled temporally and spatially varying climate variables for the Lake Erie region using spatially-detailed raster images. Monthly surface water temperatures were formed using data supplied by the Great Lakes Environmental Research Laboratory (GLERL). Similar to the algae composite data, the GLERL raster images aggregate water temperature into spatially fine units (approximately 1300 by 1300 meter squares) using remote sensing data (GLERL 2016). Daily precipitation data was also obtained from the PRISM Climate Group which forms nationwide climate raster images using data collected from monitoring stations positioned across the entire United States (PRISM 2016).[3]

Due to the continuous raster measures of algal and climate data, we explored a number of potential approaches to aggregate and attach this data to our zip code units of observation. The primary set of results discussed below are based on aggregating both the algal readings and the climate variables using the three closest locations for each zip code. Using these observations, we calculate the mean monthly Cyanobacteria Index value, Lake Erie surface water temperature and number of precipitation days[4] for every month and zip code in our study area.[5] Finally, we converted the mean Cyanobacterial index values into 0-1 indicator variables indicating whether or not algal conditions surpassed the World Health's Organization's (WHO) moderate health risk advisory threshold of 20,000 cells/mL and the high health risk advisory threshold of 100,000 cells/mL.[6] The WHO advises local communities to begin posting on-site advisory signs as soon as water conditions surpass the 20,000 cells/mL threshold; under these conditions recreators have the potential to experience both short and long term, adverse health

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[3]Unlike the algal data, both the precipitation and water temperature data were available year-round.
[4]Precipitation days refers to the number of days in which there was a non-zero amount of precipitation recorded within the area.
[5]Our results are robust to a number of spatial aggregations. Monthly maximum algal readings, algal readings taken at each zip code's closest point of entry and larger/smaller spatial aggregates have all been tested. Quantitatively similar results are derived from each of these cases and match closely with estimates discussed in section 5.
[6]The Ohio Department of Health sets their Recreational advisory threshold at 6 Microcystin µg/L (ODH 2016). Although our algae variable is measured in Cyanobacteria cells/mL, a value of 20,000 Cyanobacteria cells/mL corresponds to a value of 10 Microcystin µg/L (Chorus 1999), closely approximating the Ohio EPA's recreational advisory threshold.

outcomes (i.e. skin irritation, stomach illness, etc.) when interacting with water. Furthermore, given our personal conversations with a HAB modeler at NOAA (Wynne 2016), we assumed all observations occurring between November – May were untreated and had algal conditions that were consistently below the recreational advisory thresholds. This appears to be a reasonable assumption to make given the aggregate, mean algal readings displayed on Figure 4, the strong, positive relationship observed between water temperature and algal growth (Carey et al. 2012; Kosten et al. 2012)[7] and the tendency for Lake Erie to freeze during the winter months.

A brief description of the variables used in this study is provided in Table 1 with an accompanying set of summary statistics displayed in Table 2. Overall there are a total of 6,862 month by zip code observations used within this study, each selling on average 80 permits a month. Substantial variation exists within this measure, with some zip codes having no permit sales while others have monthly sales nearing 1,500. Similar to permit sales, water conditions also vary significantly within our study period. The average algal concentration level (36,800 cells/ml) falls above the moderate health risk advisory threshold of 20,000 cells/ml and has a standard deviation more than three times as large (119,400 cells/mL). Converted to an advisory threshold indicator, we see that 11.6% of our sample experienced moderate, algal advisory conditions. A large portion of these treated observations faced even more severe conditions with 8.7% of the sample having mean readings above the 100,000 cells/mL threshold. Controls for water temperature, rain and proximity to Lake Erie are all as expected.

Fishing licenses sold by month are plotted in Figure 5. The most common purchase month is May and there is a clear skewedness with more purchases occurring in the summer and fall months than in the winter months. Figure 6 shows the fishing permits sold by county with substantial variability across locations. As expected, the most populous county containing Cleveland, Cuyahoga County, is associated with the greatest number of permits sold. These differences suggest that in addition to algal and lake

[7]Cyanobacteria are better suited to grow when water temperatures are above 25 degrees Celsius. This is in part due to the advantage Cyanobacteria have over other phytoplankton when water columns become more stratified, which tends to occur more often when surface water temperatures are elevated (Paerl and Huisman 2008).

climate variables, it is likely important to control for time-constant differences across space, which we expand upon in the following econometrics section. Finally, we show the total number of permits sold by year in Figure 7. Compared to 2012 – 2014, approximately 8,000 fewer permits were sold in 2011. The largest HAB ever recorded on Lake Erie, caused by frequent and heavy spring precipitation events and record nutrients loads (Michalak et al. 2013), also occurred in 2011. This simple comparison is suggestive of the potential impact HABs have on the Lake Erie recreational fishing industry.

4. Model of Fishing Permit Sales

To model the discrete, non-negative distribution of our dependent variable, we assume our sample of annual fishing permit licenses are drawn from a Poisson distribution characterized by parameter $\lambda_{i,t}$:

(1) $Permit\ Count_{i,t} \sim Poisson(\lambda_{i,t})$

where

(2) $\lambda_{i,t} = Exp(X_{i,t}\beta + \epsilon_{i,t})$

and

(3) $e^{\epsilon_{i,t}} \sim Gamma(\frac{1}{\alpha}, \alpha)$

The number of permits sold in location i, during time period t is given by the term $Permit\ Count_{i,t}$, $X_{i,t}$ is a vector of observable, temporally and spatially-varying determinants of $Permit\ Count_{i,t}$, $\epsilon_{i,t}$ is a gamma distributed error term with mean 1 and variance α and β is a vector of parameters to be estimated.[8] Inclusion of both $X_{i,t}$ and $\epsilon_{i,t}$ within equation (2) transforms the standard Poisson model into a Negative Binomial model by allowing variation in $\lambda_{i,t}$ to be explained through both observed and unobserved sources of heterogeneity. Removal of the error term from equation (2) collapses the Negative Binomial model into a Possion model and forces the conditional variance of $Permit\ Count_{i,t}$ to be equal

[8]For interpretative purposes α is often referred to as the dispersion parameter. Larger values of α will result in larger gaps between the conditional mean and variance of $Permit\ Count_{i,t}$.

to its conditional mean; an unlikely assumption in most empirical settings. Given the distributional assumptions made in (3), however, the conditional variance of $Permit\ Count_{i,t}$ is less constrained and is allowed to exceed its conditional mean.[9]

We include a number of covariates within the vector of observables $X_{i,t}$ to estimate the impact higher concentrations of HABs have on fishing permit sales. The model and covariates are presented in the equation below:

(4) $\lambda_{i,t} = Exp(\beta_0 + \beta_1 AdvisoryThreshold_{i,t} + \beta_2 WaterTemperature_{i,t} + \beta_3 RainDays_{i,t}$

$+ \delta_t + \xi_i + \epsilon_{i,t})$

where $AdvisoryThreshold_{i,t}$ is a time varying 0-1 indicator variable for whether or not algal conditions exceed the WHO's 20,000 cells/mL moderate health risk advisory threshold, $WaterTemperature_{i,t}$ is a continuous measure of surface water temperature on Lake Erie while $RainDays_{i,t}$ measures the number of days where non-zero levels of precipitation were recorded. A set of spatial (ξ_i) and temporal control variables (δ_t) were further included in (4) to control for observable and unobservable time-variant and period-specific factors that influence the number of fishing permits sold. Determinants such as proximity to Lake Erie, access to fishing hot spots, differences in seasonal demand and annual changes in fishing regulations are captured by these dummy variables. Given the potential concern of omitted variable bias inclusion of both temporal and spatial controls are an essential component of our analysis, absorbing potential drivers of license purchases that if left unaccounted for could bias our estimates for the key parameter of interest, β_1.

5. Results

Results from three specifications of equation (4) are shown in Table 3. Each specification uses a different combination of spatial and temporal dummies to control for potential unobservables that could cofound

[9]Under this setting the distribution of $Permit\ Count_{i,t}$ would have a conditional mean of $\lambda_{i,t}$ and a conditional variance of $\lambda_{i,t}(1 + \lambda_{i,t}\alpha)$ (Cameron and Trivedi (1986)).

our estimates. The first column includes month and zip code fixed effects. The second column includes zip code, year and month fixed effects, while the final column contains the most stringent set of controls with zip code and year by month dummy variables. Each specification includes spatial controls which account for time-constant zip code level unobservables, while the sequentially increasing number of temporal controls (moving from left to right in Table 3) help account for time-varying unobservables that are specific to a given month or year.[10] Our preferred model in column 3 accounts for changes in seasonal fishing conditions both within and across years by including a dummy for every month during the study period.[11]

The results for our threshold indicator variable across each specification ranges from a decrease of slightly over 5% in annual permit purchases after surpassing this threshold to a decrease of approximately 10%.[12] In all cases this coefficient is significant. Other control variables have the expected sign, even after controlling for temporal patterns across and within years using month by year fixed effects, with higher water temperatures associated with more permit activity and rainy days reducing permit activity. We assume that the remainder of the drivers of purchasing patterns are absorbed by the controls outlined above.

Table 4 provides additional robustness where we examine the impact of licenses purchases as distance to Lake Erie increases. We expect that households choosing to locate closer to Lake Erie may be more adversely affected from high algal concentrations than those further away for several reasons. First, urban sorting theory suggests households with the strongest preferences for angling are, ceteris paribus, more likely to locate closer to angling locations such as Lake Erie. Second, as households are located further from the lake, the extent of possible substitutes reachable at the same cost as traveling to Lake

[10]We also run a specification that includes month and zip code by year fixed effects. Unlike the specifications used in Table 3, this model accounts for unobservables that vary annually at the zip code level which would include things such as changes in income and new development while maintaining controls for monthly differences across time. Results from this specification are significant and qualitatively similar to those discuss in the paper.

[11]A dummy variable is created for every month except February 2011, which is the omitted group.

[12]Estimates discussed in the text are converted from a difference in the logs of expected counts to a percentage using the following equation: $e^{Coefficient} - 1$.

Erie are likely to increase which would mitigate potential losses if Lake Erie water quality was poor. The results support this hypothesis. We find the greatest decrease in permit purchases for households less than 10km from the lake which exceeds 14%, while for households located between 10km and 20km those reductions fall to approximately 9.6%, and finally permit purchase losses become statistically insignificant beyond 20km. This finding is similar to that in the hedonic housing literature finding that proximity households are most adversely affected by HABs (Wolf and Klaiber, 2017).

An additional set of results, displayed in Table 5, examine the impact of varying thresholds of algal blooms on permit purchasing behavior as well as different approaches to attach algal readings to zip codes. The first column aggregates algae at the nearest public access point for each zip code to determine if anglers are more concerned with water conditions at their point of entry or at the shoreline point closest to them. The second column uses the maximum algal reading within a given month rather than the mean reading. Fishermen may pay more attention to severe water conditions instead of average conditions, especially given the media coverage dedicated to large HABs (Wines 2014; Arenschield 2015; Devito 2015). The final column includes an additional indicator variable for the high advisory threshold implemented by the WHO. Results from each of these specifications follow closely with our primary set of results presented in Table 3. In particular, the coefficients attached to the primary variable of interest, WHO's 20,000 cells/mL advisory threshold, remain between 5% and 11% across all three columns, while the additional, threshold indicator variable in the third column is insignificant. Since the two dummy advisory thresholds are additive, results from the third specification indicate there is no additional reduction in permit sales after algae conditions surpass the 20,000 cells/mL threshold.

Our final set of results test our model's functional form assumption. Columns 1 and 2 remove the assumption that permit counts are drawn from a Poisson distribution and instead are characterized by a normal or log normal distribution. Using a level-level functional form restriction, we find that surpassing a moderate advisory threshold reduces the average number of permits sold within a zip code by 7. This compares well with the 8.2[13] permits lost per zip code predicted under our favored specification, while the log-level specification estimates much higher losses of around 14 permits per zip code.[14] Finally we run a standard Poisson count data model, which assumes equidispersion of the dependent variable, and find similar results to those derived under a negative binomial setting.[15] Given the likely unreasonable restriction that the mean and variance of our permit count data is equivalent, however, we continue to use the negative binomial model as our primary specification.

6. Discussion

Climate change and increased urbanization are expected to further impair water conditions on Lake Erie through higher summer temperatures and increased nutrient enrichment from runoff. As a consequence of these exacerbated conditions policymakers will continue to grapple with where and to what extent to target policies aimed at reducing blue-green algae's harmful impacts. Before optimal management can occur, however, more information on the economic costs associated with blue-green algae is needed.

The results from this paper help to fill in this gap. Similar to other valuation results discussed in the property hedonics literature (Wolf and Klaiber 2017), harmful algal blooms impact on fishing permit purchases appears to be highly non-linear. In particular we find no additional losses are incurred after algae conditions surpass the WHO's moderate advisory threshold, suggesting there may be a disconnect between the increasing health risks associated with more frequent and intensive HABs and recreators' perception of that risk. We further find

[13]8.2 is the predicted average marginal effect from the negative binomial model.
[14]After adjusting the coefficient using the method prescribed by Halvorsen and Palmquist (1980) and multiplying it by the average number of permits sold (79.64), we find a loss of approximately 14 permits per zip code.
[15]We also ran a zero-inflated Poisson model. These results from this functional form specification are similar to those presented in the final two columns of Table 6.

these negative effects to be spatially limited; total monthly fishing permit sales are only affected by changes in Lake Erie water conditions if they occurred within a zip code located at most 20 km away from the lake.

Finally, using the coefficients recovered from our preferred model specification we predict the total reduction in permit sales caused by a hypothetical, summer-long, moderate WHO advisory. Total permit sales from each zip code are expected to drop, on average, by 8.22 for every month of poor algae conditions. Aggregating this number across all the zip codes within our study (146) and across a 3-month period, similar in duration to the 2011 algal bloom, suggests a total loss of approximately 3,600 permits and a reduction in government revenue of $68,400.[16] Lost private revenue is likely much higher. According to the U.S. Fish and Wildlife Service and the United States Census, Ohio anglers visiting the Great Lakes spend approximately $98 per trip and go fishing 6.3 days a year (2011). Results from a survey of Lake Erie anglers conducted in 2014, on the other hand, recover similar per trip expenditure estimates ($88 per trip) but find a larger number of trips are taken each year (17.6) (Sohngen et al. 2015). A 3,600 reduction in annual fishing permits would therefore imply a total loss ranging between $2,224,800 and $5,575,680 in fishing expenditures.[17] Given the expected increase in algal bloom frequency and duration over time, these findings present new information on the potential costs of algal blooms. As policymakers grapple with the appropriate response to algal blooms moving forward, estimates such as the ones developed here are timely and provide policy-relevant information that informs policymakers tasked with determining the extent and type of management strategies to employ.

[16]Annual fishing permits cost $19 in Ohio.
[17]This estimate is likely a lower bound given the likelihood that many anglers will continue to purchase permits under adverse conditions and substitute away from their preferred recreation locations. Our data on permit sales would not account for this welfare loss.

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Figure 1: Concentration of Annual Fishing Permit Sales by Zip Code

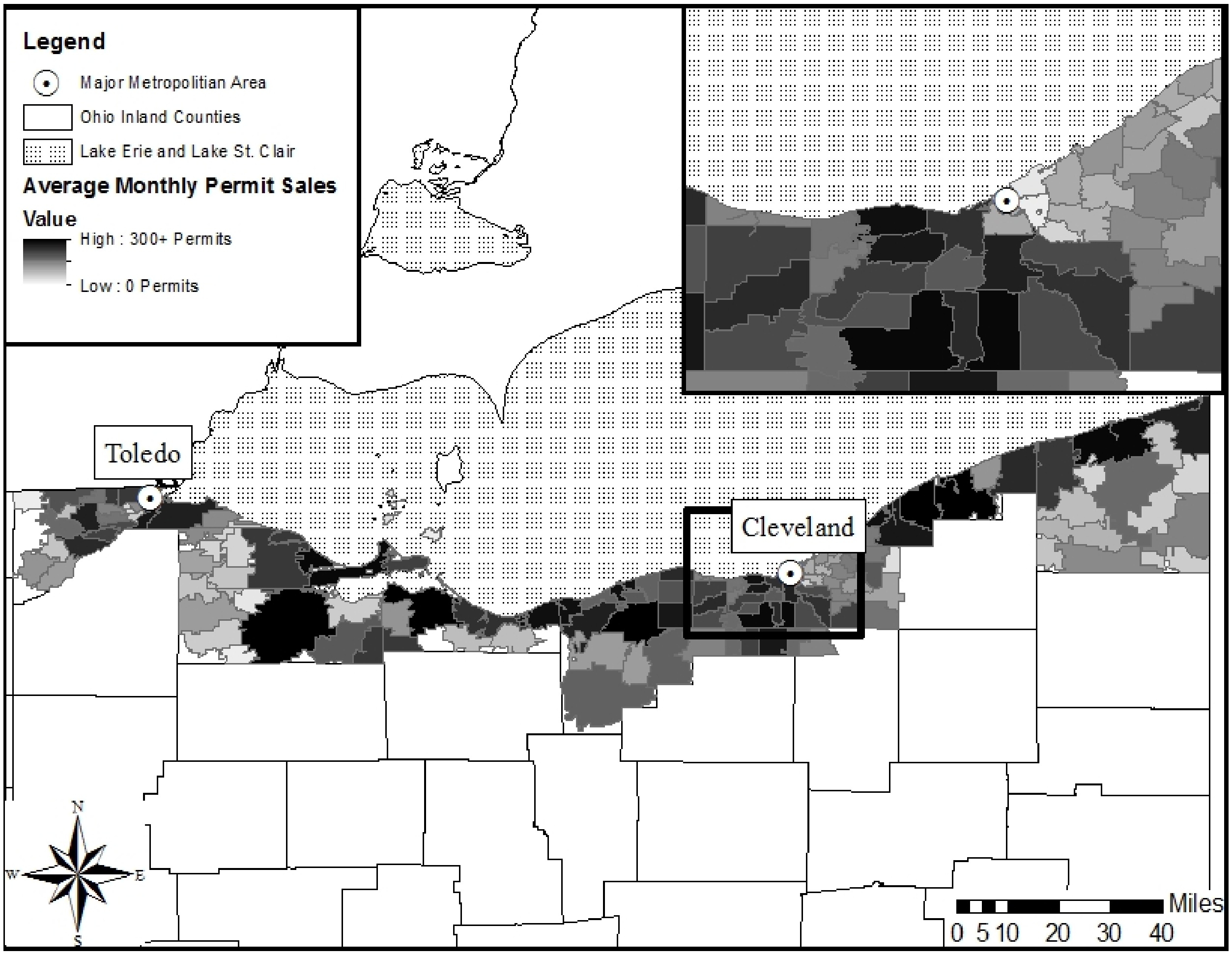

Figure 2: County and Zip Codes bordering Lake Erie – September 2011

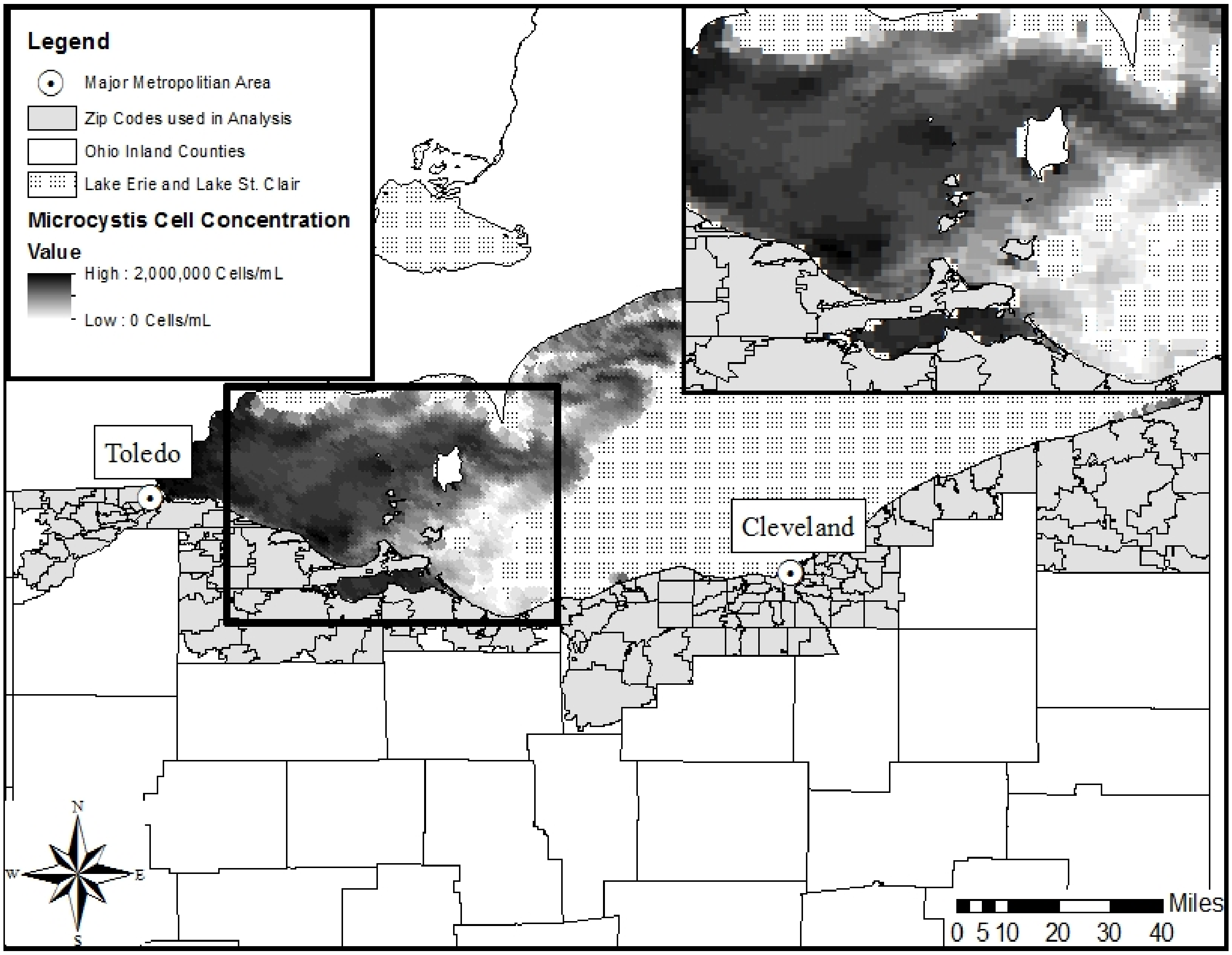

Figure 3: County and Zip Codes bordering Lake Erie – September 2012

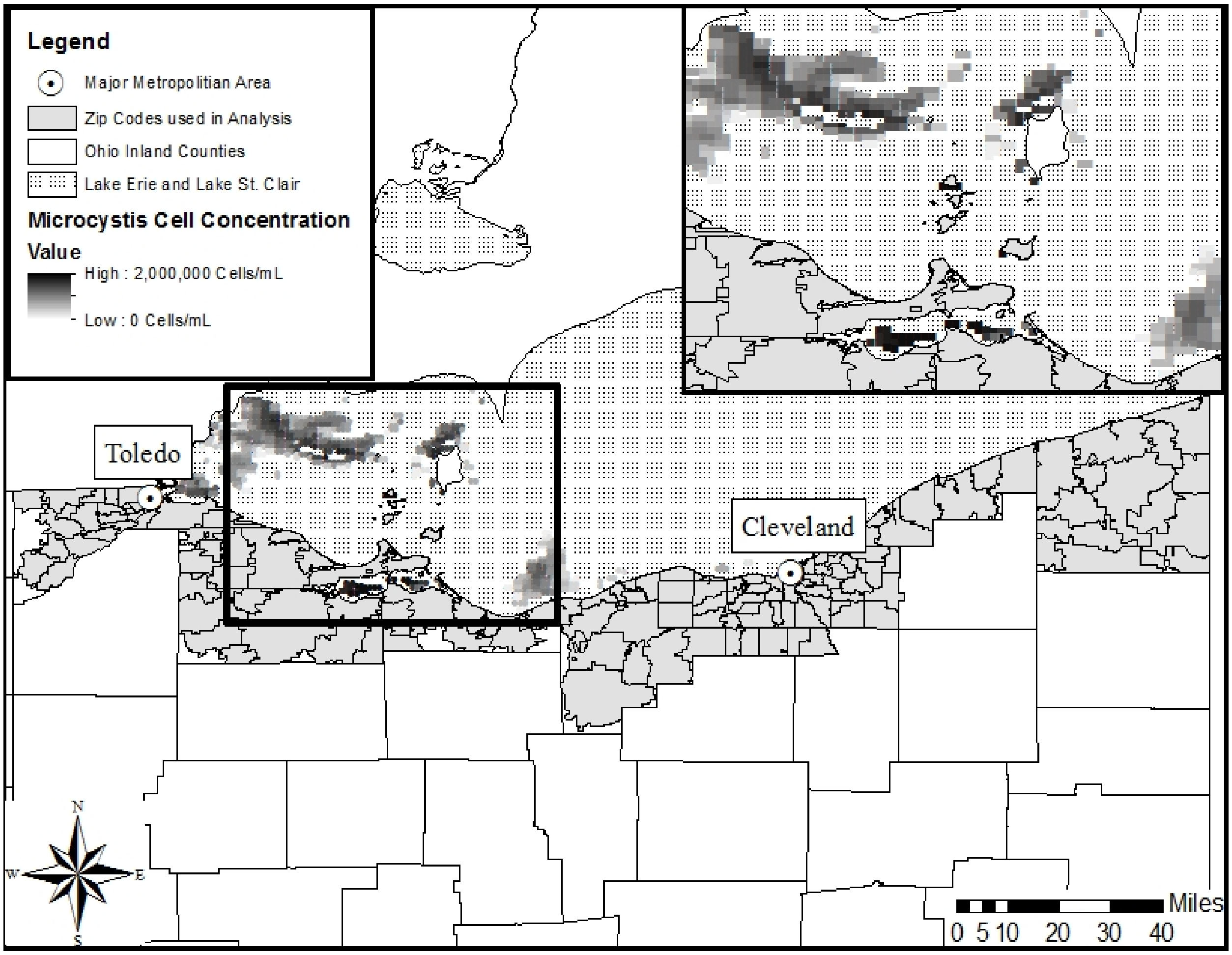

Figure 4: Mean Algal Readings by Year

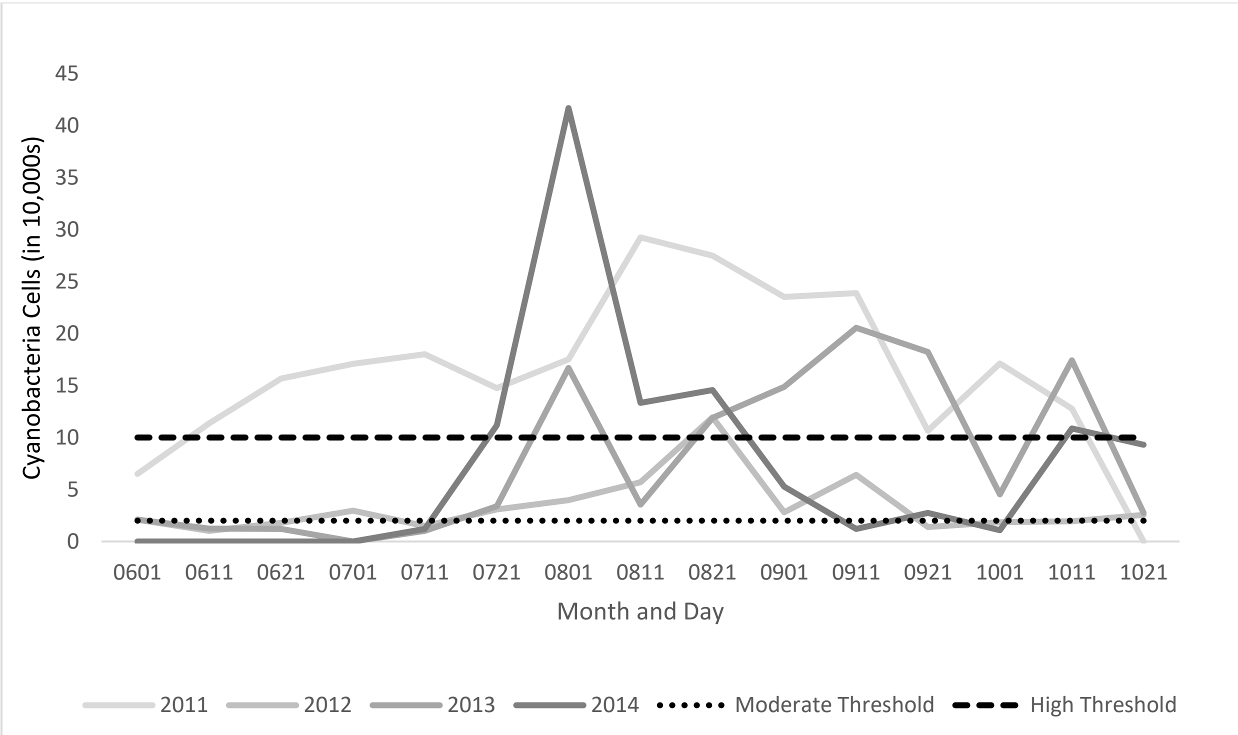

Figure 5: Fishing Permits Sold by Month 2011- 2014

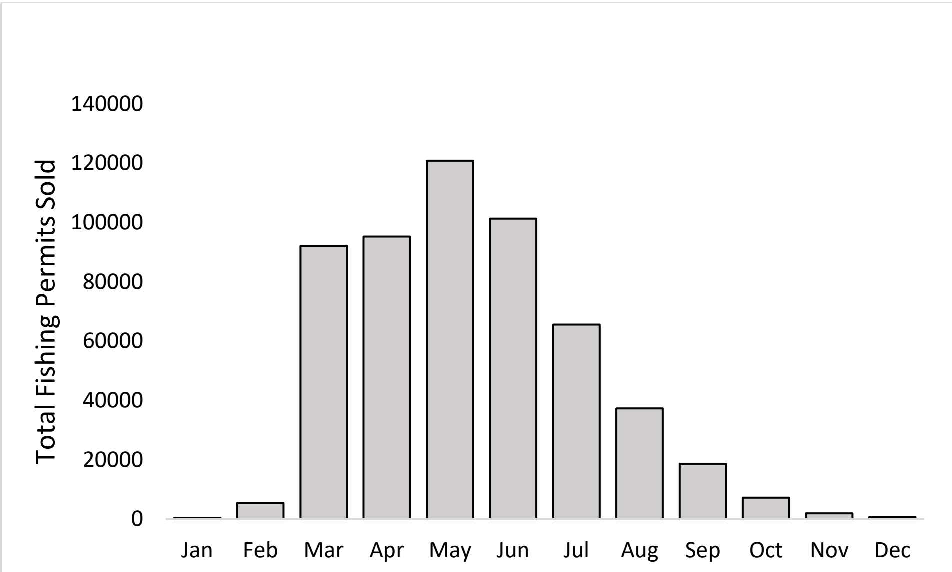

Figure 6: Fishing Permits Sold by County 2011 - 2014

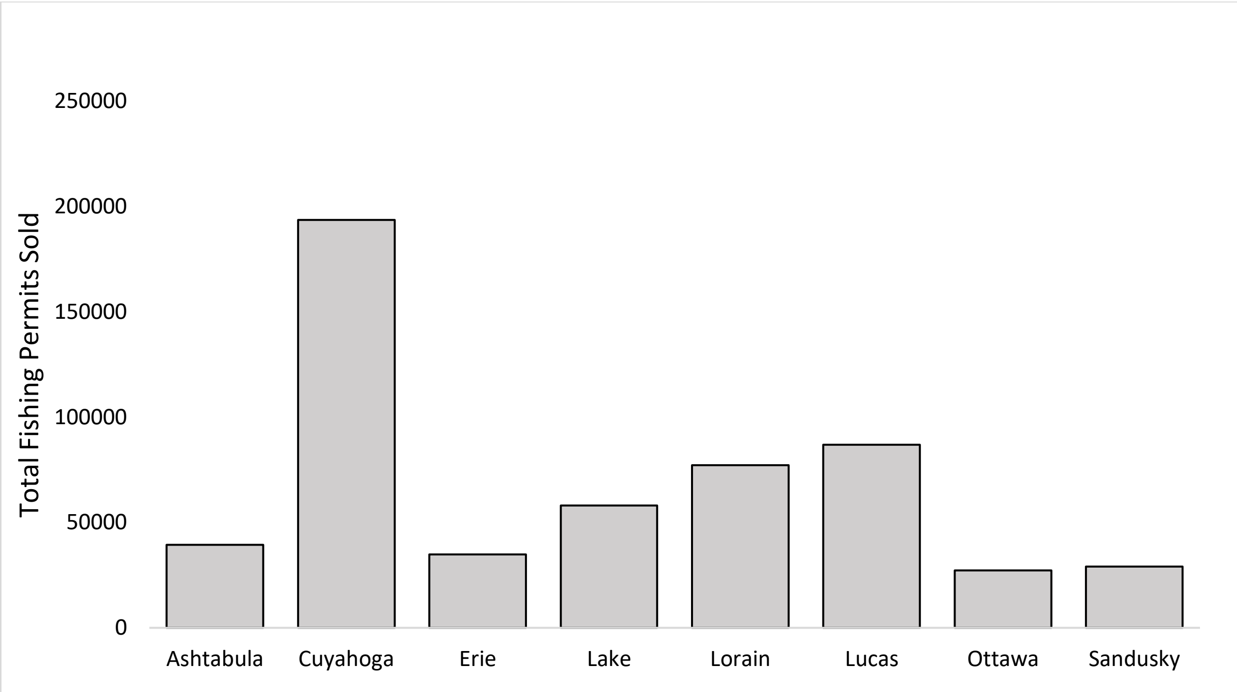

Figure 7: Total Fishing Permits Sold by Year

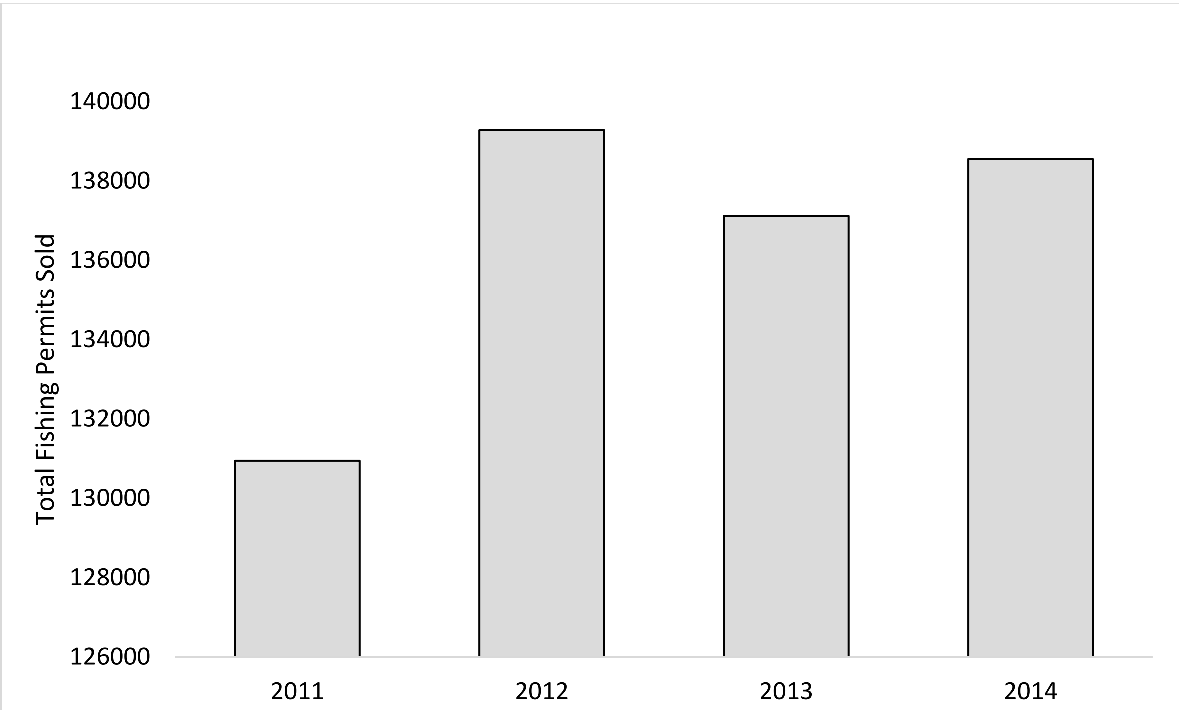

Table 1: Variable Descriptions

Variable	Description
Permit Count	Number of annual, resident fishing licenses sold within a given zipcode and month
Algae	Continuous measure of algae measured in 10,000s of Cyanobacteria cells/mL
Low Advisory Threshold	Indicator variable for WHO's 20,000 - 100,000 Cyanobacteria cells/mL Advisory Threshold
High Advisory Threshold	Indicator variable for WHO's 100,000 - 10,000,000 Cyanobacteria cells/mL Advisory Threshold
Water Temperature	Monthly mean water temperature in degrees Celsius
Rain Days	Number of rainy days within a given month
Distance to Lake	Distance from zipcode centroid to Lake Erie in 1000s of meters
Distance to Ramp	Distance from zipcode centroid to nearest public access point where boating or fishing is permitted in 1000s of meters

Table 2: Summary Statistics

	(N= 6862)			
Variable Name	Mean	Std Dev	Min	Max
Permit Count	79.64	127.30	0	1466.00
Algae (10,000 cells/mL)	3.68	11.94	0	175.80
Moderate Advisory Threshold	0.116	0.32	-	-
High Advisory Threshold	0.087	0.28	-	-
Water Temperature	12.52	8.41	0	26.91
Rain Days	14.18	3.96	4.33	26.00
Distance to Lake (1000s)	11.42	9.53	0.16	43.69
Distance to Ramp (1000s)	11.99	9.69	0.50	43.72
Sale Year	2013	1.11	2011	2014
Sale Month	6.62	3.39	1.00	12.00

Table 3: Robustness to Temporal Fixed Effects

Variables	(1)	(2)	(3)
Moderate Threshold (>20,000 cells/mL)	-0.0590**	-0.0532**	-0.107***
	(0.0242)	(0.0243)	(0.0229)
Water Temperature (Degrees Celsius)	0.0337***	0.0493***	0.0332***
	(0.00461)	(0.00522)	(0.00690)
Rain Days	0.000469	-0.00236**	-0.00594**
	(0.000997)	(0.00100)	(0.00240)
Constant	-2.584***	-2.553***	-2.574***
	(0.111)	(0.110)	(0.106)
Observations	6,862	6862	6862
Month Fixed Effects	Yes (11)	Yes (11)	No
Year Fixed Effects	No	Yes (3)	No
Month By Year Fixed Effects	No	No	Yes (46)
ZipCode Fixed Effects	Yes (145)	Yes (145)	Yes (145)

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the zipcode level. All columns use a negative bionomial functional

Table 4: Spatial Heterogeneity

Variables	<10km	10km - 20 km	>20km
Moderate Threshold (>20,000 cells/mL)	-0.151***	-0.101**	0.0397
	(0.0349)	(0.0417)	(0.0431)
Water Temperature (Degrees Celsius)	0.0321***	0.0305***	0.0163
	(0.0115)	(0.0107)	(0.0183)
Rain Days	-0.00676*	0.000471	-0.00220
	(0.00393)	(0.00332)	(0.00575)
Constant	-0.313**	-3.729***	-2.401***
	(0.142)	(0.167)	(0.314)
R-squared	-	-	-
Observations	3,807	1,692	1,363
Month By Year Fixed Effects	Yes (46)	Yes (46)	Yes (46)
ZipCode Fixed Effects	Yes (80)	Yes (35)	Yes (28)

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the zipcode level. All columns use a negative bionomial functional form.

Table 5: Spatial Aggregation and Advisory Thresholds

Variables	Ramp Measure	Max Measure	Various Thresholds
Moderate Threshold (>20,000 cells/mL)	-0.0850***	-0.0948***	-0.119***
	(0.0227)	(0.0231)	(0.0307)
High Threshold (>100,000 cells/mL)	-	-	0.0184
	-	-	(0.0274)
Water Temperature (Degrees Celsius)	0.0354***	0.0370***	0.0336***
	(0.00676)	(0.00666)	(0.00685)
Rain Days	-0.00770***	-0.00622***	-0.00594**
	(0.00276)	(0.00236)	(0.00239)
Constant	-2.553***	-2.604***	-2.577***
	(0.108)	(0.106)	(0.107)
Observations	6,862	6,862	6,862
Month by Year Fixed Effects	Yes (46)	Yes (46)	Yes (46)
ZipCode Fixed Effects	Yes (145)	Yes (145)	Yes (145)

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the zipcode level. All columns use a negative bionomial functional form.

Table 6: Specification Robustness

Variables	Level - Level Regression	Log - Level Regression	Poisson Regression	Negative Bionomial Regression
Moderate Threshold (>20,000 cells/mL)	-6.929**	-0.197***	-0.137***	-0.107***
	(3.314)	(0.0480)	(0.0176)	(0.0229)
Water Temperature (Degrees Celsius)	-1.444	0.0136	0.0183***	0.0332***
	(3.771)	(0.0174)	(0.00553)	(0.00690)
Rain Days	-1.361**	-0.0152***	-0.000875	-0.00594**
	(0.677)	(0.00563)	(0.00233)	(0.00240)
Constant	28.99*	0.709***	-2.576***	-2.574***
	(17.51)	(0.159)	(0.128)	(0.106)
Observations	6,862	6,862	6,862	6,862
R-squared	0.653	0.926	-	-
Month by Year Fixed Effects	Yes (46)	Yes (46)	Yes (46)	Yes (46)
ZipCode Fixed Effects	Yes (145)	Yes (145)	Yes (145)	Yes (145)

Notes: ***, **, * indicates significance at the 1%, 5% and 10% level respectively. Standard Errors have been clustered at the zipcode level.