The Presence of Above Standard Levels of Commonly Tested Contaminants in Communiites on Long Island, New York: The Impact of Income on Untreated Water Quality

Amy Catalano
Hofstra University, amy.catalano@hofstra.com

Michael A. Marino Ed.D.
Molloy College, mmarino1@molloy.edu

eISSN 2345-0363
Journal of Water Security, 2019, Vol. 5
Article Number: jws2019001
DOI: https://doi.org/10.15544/jws.2019.001

THE PRESENCE OF ABOVE STANDARD LEVELS OF COMMONLY TESTED CONTAMINANTS IN COMMUNITIES ON LONG ISLAND, NEW YORK: THE IMPACT OF INCOME ON UNTREATED WATER QUALITY

Amy Catalano[a], Michael Marino[b]

[a]*Teaching, Learning and Technology Department, Hofstra University, 251 Hagedorn Hall, Hempstead, New York, USA. E-mail: Amy.Catalano@Hofstra.edu*

[b]*Department of Biology, Chemistry and Environmental Studies, Molloy College, Rockville Centre, New York, USA*

Submitted 22 January 2019; accepted 20 May 2019

Abstract. Water quality is a pressing issue in many communities. Long Island (LI), New York, rests on a system of aquifers created by prehistoric glacial activity. These aquifer systems are the only source of drinking water for LI. Water quality issues are pervasive in the region due to nitrate pollution, caused by antiquated septic systems in much of the Island, as well as the prevalence of environmental clean-up sites. Using the Watertraq database, we searched for levels of select compounds that were present in wells above acceptable levels on LI. We then collected demographic data from the U.S. Census, including income, ethnicities, poverty levels, number of children, senior citizens and renters for towns in parts of two counties on LI to determine whether there was a relationship between the presence of above standard levels of compounds and income. Using an Ordinary Least Squares (OLS) regression we found a statistically significant negative impact (at the $p < 0.01$ level) of income on the presence of contaminants in untreated water. In other words, the lower the income of the region, the greater the chance that above standard levels of volatile organic compounds were present.

Keywords: contaminants, minorities, socioeconomic status, untreated water, water quality.

Introduction

Water quality is a pressing issue in many communities. Even where water authorities test regularly, natural disasters, the presence of Superfund sites, illegal dumping, and improper disposal of household chemicals, among other causes, can impact the qualities of raw or untreated groundwater. Recent events in communities such as Flint Michigan, indicate that the impact of poor water quality may be greater in low-income communities or in minority communities (Calderon *et al*., 1993; Sherwin, 2017; van Derslice, 2011).

Long Island (LI), New York, rests on a system of aquifers, some of which were created by prehistoric glacial activity (Brown, Schoonen, 2003). These aquifer systems are the only source of drinking water for LI. Water quality issues are pervasive in the region due to nitrate pollution, caused by antiquated septic systems in much of the Island, as well pollution resulting from the prevalence of Superfund sites, are designated by the U.S. government as environmental clean-up sites that are contaminated by hazardous waste. We posit that the extreme wealth disparities on LI are related to the variation in untreated water quality. LI is home to some of the most affluent communities in New York given its proximity to NYC, however, income disparities are widespread. Using Watertraq, a website developed by the LI Commission for Aquifer Protection (LICAP), we searched for levels of select contaminants that are present in wells above acceptable levels on LI. Acceptable levels were defined by the Maximum Contaminant Levels (MCL) posted on the Watertraq website. We then collected demographic data, including income, ethnicities, poverty levels, number of children, senior citizens and renters for each town or village in one county, and parts of another, on LI to determine whether there was a relationship between the presence of above standard levels of compounds and income. Particularly, we looked at the presence of volatile organic compounds (VOCs) considered harmful to human health. VOCs are organic gases that release into the air through "off-gassing". Exposure to VOCs to can result in respiratory irritation or skin irritation. While long term exposure, for some chemicals, can lead to cancer, damage to the central nervous system, liver or kidneys.

Because the data for this study is from testing done on untreated, raw water, that will not be consumed by residents, the implications for untreated contaminated water are unclear (Squillace *et al*., 1999). On LI, residents do not typically drink untreated water, and all wells sampled for this study are under the jurisdiction of a water district responsible for testing and treating. Studies conducted by the Environmental Protection Agency (EPA) however, found that even treated drinking water may have traces of contaminants in the water, although negative health effects are unlikely after treatment (EPA, 2018). While the literature on water quality is vast and wide, the following review of research focuses on water quality studies conducted on LI and studies on sociological, educational, and economic factors that impact water quality.

The United States Geological Survey (USGS) regularly reports data on water quality indicators. Additionally, researchers have made attempts to connect explanatory variables to these indicators or the presence of contaminants. Most relevant to the present study, Squillace *et al.* (1999) assessed 60 VOCs in untreated water across the U.S. excluding areas of known contamination from more than 3000 wells. Although concentrations of VOCs were low, 47 percent of wells had at least one VOC. EPA drinking water standards were exceeded in 6.4 percent of wells and 2.5 percent of drinking wells. Solvent compounds and methyl tert-butyl ether were the most frequently found VOCs, which has since been banned for use in gasoline in New York state. Further, population density was a significant predictor of VOC presence in wells. Their regression model indicates that about 7 percent of all ambient groundwater in the United States likely have at least one VOC present at a level of 2 μg/l.

Water quality on Long Island, New York

Attempts to gauge water quality on LI have focused on the suspected impact of the agricultural industry in the region and population density. Watson *et al*. (2018) examined nutrient pollution in LI estuary environments using nutrient stoichiometry and stable isotope ratios in estuary soils around the coasts, and found that all coastal water bodies are polluted with nitrogen. Pollution was strongest in the most densely populated areas of LI (Western LI) as compared to Eastern LI. Using Structural Equation Modelling the authors determined that population density, plus salinity, longitude, land use, and waste water treatment plants accounted for 61 percent of the variance in the model of the composite chemical index, meaning that those variables most significantly predicted the presence of chemicals in estuaries. Additionally, they indicated that poor water quality on LI is due to higher population density, geographic isolation, and antiquated septic systems. As noted by Watson *et al*. (2018) ground water is the only source of drinkable water on the island, and water quality issues are exacerbated by use of fertilizer and atmospheric deposits coming from burning fossil fuels.

In an earlier study on the impact of land use on water quality on LI, Eckhardt, Stackelberg (1995) used the USGS WATSTORE (the National Water Data Storage Retrieval) system to analyze the chemical quality of the upper glacial aquifer in LI from 1978-1984 as it relates to ten types of land use in a sample of 903 wells. Most relevant to the current study, high levels of VOCs were found near industrial or commercial areas, but were also found in highly populated residential areas as well. Undeveloped or low population regions had the lowest levels of all chemicals except for chlorides and total dissolved solids. Most salient to the current study was that they found tetrachloroethylene in 20 percent of wells. They noted that "An understanding of the effect of human activities on the quality of water in the aquifer system is essential to the development of water-management plans by local agencies when talking about land use and water quality" (p. 1028). While the research evaluating LI water quality varies with respect to types of wells or water bodies, they highlight the characteristics that impact untreated water quality in the region. Primarily, population density and industry are the largest contributing factors to contaminants or pollutants in water despite whether levels were above or below MCL.

Socioeconomic status and water quality

Across the United States, in low-income regions contaminants in drinking water are not uncommon. Similar to the present study, Balazs *et al*. (2012) hypothesized that lower income communities serving minorities were more likely to have higher levels of arsenic in drinking water. Examining 464 community water systems serving low income residents in the San Joaquin Valley in California, the researchers found that higher rates of home ownership were related to lower arsenic levels in their drinking water. Additionally, those water systems serving more low-income minorities had greater violations of a MCL and higher levels of arsenic.

To determine the impact of educational initiatives and testing promotions on residents' likelihood to test their drinking water for contaminants if given a testing kit, Flanagan *et al*. (2010) surveyed 670 randomly selected households in New Jersey. Respondents reported higher rates of testing in communities where there was more testing promotion. In addition, communities with higher incomes and higher levels of education were associated with higher rates of testing. Residents with a Bachelor's degree were ten times more likely to test their water when offered free tests, while 47 percent who accepted the test had a higher income and higher education level, indicating that despite targeting initiatives to promote water testing and free supplies, those with more education and higher incomes were more likely to benefit from the initiatives because they were more likely to accept them.

Private water supply systems are primarily used in rural areas that may often be underserved. To determine quality of private water systems, Smith *et al*. (2014) analysed 828 samples at the "point-of-use" from homes using private water supplies in Virginia to determine relationships between the presence of faecal indicator bacteria and income and education. They found coliform in 42 percent of the samples and *E. coli* in 6.6 percent. The authors noted that possible contamination came from human septage in some of the samples for homes that tested positive for coliform. They also note that these areas also tend to lack education on environmental issues, thereby making the case for targeted efforts at education in these more vulnerable areas.

Like the present study, Farzin, Grogan (2013) investigated the socioeconomic factors related to water quality in California over a 13-year period using 24 water quality indicators, including the presence of contaminants. They tested Environmental Kuznets Curve (EKC) theory which states that, at first, as income increases, the quality of the environment decreases, but after a certain per capita income level the environmental quality begins to increase. Their results revealed that in California agricultural activity significantly and positively impacted water quality. That is, for every dollar increase in crop production, there was a decrease in some levels of contaminants (e.g., cadmium). Additionally, education was an indicator of better water quality.

Examination of other variables revealed that overall, minorities were not affected by poor water quality more so than Caucasians, although the authors explain that other studies examining ethnicity and water quality do so by comparing census blocks (as in the current study), whereas Farzin and Grogan (2013) examine relationships between towns. Additionally, higher percentages of children aged 4 and under was associated with increases in TSS (total suspended solids) and manganese, although copper and arsenic were reduced, likely due to concern about the impact of the latter contaminants on children's development. Ultimately, however, they did not find statistically significant relationships between income and water quality, although they explain that in California income levels are greater than the maximum levels reported in other studies that supported EKC theory.

Although the relationship between water quality and income has been widely investigated in underdeveloped nations, and in several case studies across the United States, no such study has been conducted on LI, NY. This study contributes to the conversation on water quality, and quantifies the extent to which contaminants in untreated water are more likely to present among specific demographic groups over others, including populations that include children, senior citizens and renters. Residents require education not only about the presence of these chemicals, but how they got there, and how they impact drinking water systems and the environment surrounding their homes.

Methods

In order to link levels of compounds in LI water systems to demographic variables, we collected water contaminant data through Watertraq, a website created by the Long Island Commission on Aquifer Protection (LICAP, 2017). We sought to collect levels of any compound reported to be above MCLs (also called "above standard") in any town in which it was reported for the years 2015, 2016 and 2017 – which include all of the years of available data. Three searches were conducted in Watertraq using the parameters "2016 LI Aquifer Sample Point ABOVE STANDARD (non-drinking)" option (with the year changed for each search). For 2015 a total of 2020 entries were found, 2016 there were a total of 3878 entries, and for 2017 a total of 3015 entries. Each of the individual data points on chemicals, levels of contaminants, town names, and well numbers were recorded in an Excel spreadsheet. Above standard is defined as a compound present in untreated water samples above a level that is safe, as determined by the EPA. For most VOCs, the MCL is 5 μg/l. We chose to only include towns that were above standard levels on VOCs that could impact human health.

Demographic data were collected from American Fact Finder (American Fact Finder, 2018). Data points included median income, poverty level, percentage of White, Hispanic, African-American, and Asian residents, percentage of children, senior citizens, and renters, and the median age of residents. Village names presented in Watertraq, were also used to retrieve the Census data designated under the Census Designated Place (CDP). Nearly all villages named in Watertraq had a CDP counterpart on Census website, allowing us to accurately match demographic data to the water quality data in each location. We also searched the NY Newsday database of environmental clean-up sites to determine whether environmental clean-up sites were in, or adjacent to, these towns (Newsday, 2017). Presence in or adjacent to an environmental clean-up site was coded as a binary predictor variable.

Nassau and Suffolk counties comprise LI, NY, a relatively affluent suburb of New York. Nassau is made up of several large towns, in which there are incorporated and unincorporated villages. We organized the data according to how testing samples were presented in Watertraq, that is by village. In Nassau, each town and in some villages, there is a different water authority, whereas in Suffolk county, there is one water authority, as well as several water districts for the entire county. The Suffolk County Water Authority (SCWA) serves 85 percent of Suffolk County. This study focuses on non-SCWA districts due to differences in data collection methods by the individual districts in the larger water authority.

Data analysis

Because levels of contaminants above maximum level varied quite a bit, from just over the MCL (typically 5 μg/l) to upwards of 400 μg/l in some towns, we chose to create a dummy variable to categorize towns as above standard or not above standard based on whether the town had at least one VOC at above standard level during testing in the years 2015, 2016, and 2017. This variable was used as the dependent variable in an ordinary least squares (OLS) linear regression. The primary aim of this study was to describe the state of water quality and its relationship to income and other related variables. Therefore, we described the income and poverty levels, number of children, senior citizens and renters, as well as ethnicities in each town that is above standard – reporting descriptive statistics. We then conducted an OLS regression, using above standard/not above standard as the dependent variable to determine whether there was a significant relationship between the presence of above standard contaminants and these demographic variables.

Results

In all 81 communities were included in the data analysis. In 2016, 2017, and 2018, 28, 17, and 26 towns reported ASLs of VOCs, respectively. Sixteen of those towns were found to have ASLs of VOCs all three years. All but two towns were in Nassau County (Western LI). Table 1 reports the communities afflicted.

Table 1. Communities with above standard levels (ASLs) of VOCs

Community	2015	2016	2017	ASLs for all three years
Albertson	X	X	X	X
Bellerose	X	X	X	X
Bethpage	X	X	X	X
Dix Hills	X		X	X
Farmingdale		X		
Floral Park	X	X	X	X
Franklin square		X	X	
Freeport	X			
Garden City	X	X	X	X
Garden city Park	X	X	X	X
Great Neck	X		X	
Glen Cove			X	
Greenlawn	X	X	X	X
Hampton Bays	X			
Hempstead	X	X	X	X
Hicksville	X	X	X	X
Jericho	X	X	X	X
Locust Valley	X			
Long Beach	X			
Manhasset-Lakeville	X	X	X	X
Merrick	X			
Mineola	X	X	X	X
New Hyde Park	X	X	X	X
Old Westbury			X	
Oyster Bay	X		X	
Plainview	X		X	
Port Washington	X		X	
Roslyn	X		X	
South Floral Park	X	X	X	X
South Huntington	X		X	
Stewart Manor	X	X	X	X
Westbury	X			
Williston Park			X	
Total	28	17	26	16

Table 2 reports the averages of demographic variables in above standard level towns (ASLs; n = 33) with non ASLs (n = 48). ASLs have a greater than average population as compared with non-ASLs. More specifically, the total population of an ASL community is 524,746, whereas the total population of non-ASL communities is 255, 281. Additionally, ASL communities have a higher mean poverty level (6 percent), lower median income ($100,077) than those with no ASLs ($115,160). Further, ASL communities have higher percentages of black and Hispanic residents.

An Analysis of Variance (ANOVA) revealed that there were significant differences in income between the ASL group and the non-ASL group (79, F = 25.3, df = 1, $p < 0.0001$).

Alternately, there were no significant differences of children and seniors in either group indicating that these populations are not impacted more in these communities than in the non-ASL's. With respect to housing, in ASL communities, 24.5 percent of homes are renter occupied as opposed to 14.9 percent of the non-ASL towns.

In order to determine which predictor variables were most likely to be associated with above standard levels of VOCs for all three years an OLS was used. The OLS included a binomial dependent variable: ASL and non-ASL. Predictor variables included: income, poverty level (highly correlated with income), race (black, white, Asian, Hispanic/latino(a), percent of children, percent of senior citizens in the town, and percent of rentals in the town. For all three years, analysis of the collinearity statistics demonstrated a variance inflation factor (VIF) value of 10.3 for the percentage of black citizens, and 16.086 for the percentage of white citizens as a predictor variable (in 2016 for example). Large VIF values indicate that the variables are highly correlated to other variables in the model. The models were then run again with all race variables removed. For all three years, income was a significant predictor of ASL status. In the year 2017 percentage of senior citizens in the community was also a significant predictor.

Table 2. Comparison of mean levels on the demographic variables in communities in the population with above standard and with no reported above standard levels of compounds

Village	N	Population	Income	Poverty level	% Black	% Hispanic	% Asian	% White	% Children	% Seniors
Average of all above standard communities	33	16,448	100,077	5.4	9.5	14.2	13.25	72	24	15
Average of all non-above	48	5,318	151,160	4.1	2.8	8.1	9.6	86	24.	18
Average of entire population	81	9,629	131,095	4.7	6	11	11.3	80	24	17

For 2015 income was a significant predicator at the $p < 0.001$ value. The unstandardized Beta weight for income was -4.184 (Table 3). Table 4 reports the demographic characteristics of all towns that were above standard on at least one VOC (n=33).

Table 3. OSL table of coefficients for predictors of above standard levels of VOC, 2015

	B	Std. Error	Beta	*t*	Sig.	Lower bound	Upper bound	Tolerance	VIF
Constant	0.894	0.137				0.621	1.168		
Income	-4.184E-6	0.000	-0.433	-4.264	0.000	0.000	0.000	1.000	1.000

Table 4. Population and income of communities with above standard levels of VOCs for 2015, 2016, and 2017

Town	Population	Median income	% at poverty level	% Black	% Hispanic	% Asian	% White	% of Children	% of Seniors	Near or adjacent to an environ-mental clean-up site
Albertson	5,182	107,450	1.9	1	8.2	23.2	73.3	21.9	20.3	No
Bellerose	2198	106550	0.4	9.4	25.8	30.2	51.5	60	4.9	Yes
Bethpage	16,429	99,423	2.8	0.9	6.5	6.2	91.5	21.4	20.5	Yes
Dix Hills	26,892	141,250	2.6	4.9	5.8	14.8	78.1	27.4	13.8	Yes
Farmingdale	8,189	73,750	5.3	2.1	12.6	8.3	84.2	18.2	16	Yes
Floral Park	15,863	100829	2.7	1.5	11.5	6.7	89.6	23.1	14.8	No
Franklin square	29,320	96,568	5.4	4.4	17.7	11.3	75.9	21.2	17.4	Yes
Freeport	42,860	72,574	13.8	40.2	41.9	2.3	54.5	23.4	12	No
Garden City	22,371	153,506	3.9	1.4	4.3	3.5	95.3	26.4	16.4	Yes
Garden city Park	7,806	98,621	3.1	1.5	11	42.6	50.2	21.4	18	Yes
Glen Cove	26,894	68,362	14.6	9.9	27.8	4	65	27.2	12.5	Yes
Greenlawn	13,742	86,563	6.7	15.9	13.3	4.1	76.7	25.6	16.6	No
Hampton Bays	13,603	75,606	6.6	1.5	29.5	1.2	95.3	21.6	14.7	No
Hempstead	53,891	55,417	20.7	49.9	42.3	2.2	19.8	25.6	9.5	Yes
Hicksville	41,547	95,030	4.4	3.8	16	22.8	71.3	21.1	15.1	Yes
Jericho	13,567	140,242	5.1	2.7	1.8	34.2	64.4	24.7	17.1	Yes
Locust Valley	3,406	85,536	3.6	3.6	12.4	1.5	84.5	26.4	13.2	No
Long Beach	33,275	84,831	7	6.2	16.4	2.7	97	16.3	16.1	Yes
Manhasset-Lakeville	8,080	107,283	5.1	10.3	12.2	11.5	74.4	25.9	18.5	No
Merrick	22,097	147,572	3.2	1.5	5.9	3.4	94.4	60.7	7.3	No
Mineola	18,799	88,594	5.9	2.6	21.5	11.2	77.1	19.4	14.7	Yes
New Hyde Park	9,712	103,811	3.7	1.7	14.6	33.3	61.2	21.5	16.2	Yes
Old Westbury	4,671	168,750	3.2	9.9	7.7	19.8	68.4	17.2	11.1	No
Oyster Bay	6,706	92,952	2.9	16.7	4.1	3.7	87.9	20.5	3.7	Yes
Plainview	26,217	132,625	3.8	0.7	4.0	1.8	87.9	24.1	17.4	Yes
Port Washington	3,154	106,902	2.4	6.1	4.2	8.3	86.8	21.5	26.1	Yes
Roslyn	2,770	87019	7.9	1.3	5	12	87.3	16.1	23.4	Yes
South Floral Park	1,764	91,250	3.5	63.6	23.7	11.2	15	24	13.	No
South Huntington	9,422	101,189	8.1	2.8	8	6.8	88.9	21.8	17.5	No
Stewart Manor	1,896	112,917	1.	2.6	11.3	5.4	87.7	23.4	19.7	No
Westbury	15,146	85,510	7.1	23	27.3	6.7	57.9	20.1	14.7	Yes
Williston Park	7,287	104,198	2.6	1.1	6.1	13.	85.4	59	9.7	No
Average of all above standard communi-ties	16,448	100,077	5.4	9.5	14.4	11.3	74.5	26.1	15	-

In other words, for every reduction in dollars of income, the likelihood of living in a community with an ASL of a VOC in untreated water increases nearly 4 times. In 2016 income was a significant predictor at the $p < 0.01$ with an unstandardized Beta weight of -2.069, similarly meaning that a decrease in dollars of income increases the likelihood of living a town with ASLs of VOCs (Table 5).

Table 5. OSL table of coefficients for predictors of above standard levels of VOC, 2016

	Unstandardized coefficients		Standardized coefficients	*t*	Sig.	95.0% Confidence interval for B		Collinearity statistics	
	B	Std. Error	Beta			Lower bound	Upper bound	Tolerance	VIF
Constant	0.552	0.124		4.457	0.000	0.305	0.798		
Income	-2.609E-6	0.000	-0.315	-2.950	0.004	0.000	0.000	1.000	1.000

Lastly, for 2017, income and percentage of senior citizens were significant predictors of ASLs, with income significant at the $p < 0.01$ level and seniors at the $p < 0.05$ level (Table 6). The unstandardized Beta weights are -3.264 for income, and -0.022 for senior citizens. In other words, for every reduction in dollars of income, the likelihood of living in a community with an above standard level of a contaminant in untreated water increases nearly 4 times. Additionally, towns with fewer senior citizens were less likely to live in an ASL community. Analysis of R^2 values shows that the 2017 model (senior citizens and income) accounts for 17 percent of the variance in ASL status, meaning the other 77 percent of ASL status is predicted by other variables not included in this analysis. For 2016 the R^2 value was 0.099 (9 percent of the variance), and for 2015 the R^2 value was 0.187 (explaining 19% of the variance).

Table 6. OSL table of coefficients for predictors of above standard levels of VOC, 2017

	Unstandardized coefficients		Standardized coefficients	*t*	Sig.	95.0% Confidence interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower bound	Upper bound	Tolerance	VIF
Constant	1.184	0.245		4.824	0.000	0.691	1.676		
Income	-3.264E-6	0.000	-0.317	-2.536	0.014	0.000	0.000	0.999	1.001
Seniors	-0.022	0.011	-0.257	-2.050	0.045	-0.043	0.000	0.999	1.001

On average four to six compounds were found for each site. The communities with the highest number of compounds were Garden City, Hicksville, Jericho, and Bethpage – all were either near or adjacent to an environmental clean-up site. (Jericho is located adjacent to Hicksville in which there is a Superfund site). The most common VOCs were carbon tetrachloride, cis-1,2- dichloroethene, 1,1-dichloroethane, tetrachloroethene, and trichloroethen. Table 7 names and describes each of the VOCs, and its likely origins.

Table 7. Uses and health effects of top compounds found in ASL communities (EPA, 2016)

Top compounds found in ASL communities	Negative health effects	Uses
Carbon Tetrachloride	May be fatal if inhaled, absorbed through the skin or swallowed. Causes eye, skin, and respiratory tract irritation. Cancer suspect agent. May cause liver, kidney or central nervous system (CNS) damage.	Dry cleaning agent, fire extinguisher, solvent; CFC propellant.
Cis-1,2-Dichloroethene	Leads to breathing difficulties. Inhalation of high vapor concentrations may cause symptoms like headache, dizziness, tiredness, nausea and vomiting.	Used to produce solvents
1,1-Dichloroethane	CNS depression, symptoms of inebriation, and respiratory effects.	Mainly used as a co-monomer in the polymerization of vinyl chloride, acrylonitrile, and acrylates. It is also used in semiconductor device fabrication for growing high purity silicon dioxide (SiO_2) films.
Tetrachloroethene	Neurological effects; liver damage, kidney effects, immune and hematologic effects, and negative effects on development and reproduction.	Solvent, degreaser, paint stripper, and used in dry cleaning, and degreaser.
1,1,1-Trichloroethane	The major effects include hypotension, mild hepatic effects, and CNS depression. Mild motor impairment and ataxia have been reported in acutely exposed humans.	Solvent, degreaser, used in cleaners, aerosol products, and glues. It is also used as a chemical intermediate in the production of vinylidene chloride.
Trichlorofluoromethane	Overexposure may cause dizziness and loss of concentration. At higher levels, CNS depression and cardiac arrhythmia may result from exposure.	Refrigerant.
Chloroform	CNS depression.	Used as a reactant with hydrogen fluoride to give monochlorodifluoromethane (CFC-22), a precursor in the production of polytetrafluoroethylene (Teflon). It is also used as a solvent and anesthetic.
Trichloroethene	CNS depression; effects on liver and kidneys and skin have also been noted.	Degreaser, solvent and refrigerant.
1,1-dichloroethene	CNS depression, symptoms of inebriation, and respiratory effects.	Used to produce chloride copolymers to produce flexible films for food packaging (i.e., SARAN and VELON wraps).
Dichlorodifluoromethane	CNS depression, difficulty breathing.	Sold as Freon-12; used as a refrigerant and aerosol spray propellant.
1,1 Dichloroethane	Ingestion may be fatal. At sufficiently high doses the material may cause liver and kidney damage.	Used as an intermediate in the manufacture of chemicals such as vinyl chloride and 1,1,1-trichloroethane, and to manufacture high vacuum rubber.
Toluene	CNS dysfunction.	Used in gasoline and as a solvent.
Methylene chloride	Effects CNS.	Solvent in paint strippers and in the manufacture of drugs. Also used a metal cleaner and solvent in electronics.

Although testing intensity is not necessarily an indicator of quality, frequent testing may indicate a prior detection of contaminant. A logistic regression with ASL nonASL as the outcome variable, and number of tests as the predictor variable, revealed that there were no significant relationships between frequency of testing and the presence of above standard levels.

Discussion

The study investigated the relationship between demographic variables, particularly those related to socioeconomic status, and the presence of commonly tested compounds in untreated water in LI, New York. A linear regression analysis indicated that towns with lower incomes had reported above standard levels of at least one VOC for each of the three years of data collection. These results make sense within the context of the communities' proximity to environmental clean-up sites and industrial activity. Environmental clean-up sites, such as Superfunds, are typically located in economically depressed areas that need the funds for economic development (EPA, 2017a). As Farzin, Grogan (2013) note, although EKC theory posits that as income increases after a certain level, so too does the quality of the environment likely because there is more money to invest in technology to control pollution, and greater demand for testing and better water quality in general.

Further, ASL towns were home to more black and Hispanic residents than non-ASL towns. Despite the fact that children and seniors are not overrepresented in ASL towns (except for seniors in 2017), children do comprise 22.9 percent of the population in these towns and implications for this vulnerable population should be considered. Additionally, renters are also more numerous in ASL communities. They too may be a vulnerable population as they may not be aware of water quality issues due to possible temporary residency, low income, or their reliance on landlords for information and care of the residence.

While we did not find a significant relationship between testing intensity and income, multiple tests in a community for a particular compound is more likely to be conducted because of the presence of compounds in the past. For example, Greenlawn tests for 1,4-dioxane more times than any other town (14 times) but had relatively low mean levels of the compound.

On LI, residents do not typically drink untreated water, and all wells sampled for this study are under the jurisdiction of a water district responsible for testing and treating. However, in some regions of the United States contaminated water has been left untreated or residents may drink from private wells that are not regularly tested or treated (Ross, 2017). The EPA states that residents who drink from private drinking wells should test water regularly and be aware of the potential contaminants (EPA, 2018). Additionally, as can be seen in Table 4, many of the ASL towns were in or adjacent to an environmental clean-up site (some were Superfund sites, supported with federal funding). Table 7 provides the list of contaminants found in the untreated water, the negative health effects related to exposure, and uses for the compounds. Most of the compounds had origins in industrial, dry cleaning, manufacturing, or a gas plant. Most were either solvents or used in dry cleaning. Nassau county has a high rate of industrial areas and dry cleaners (given its proximity to NY city), thus the presence of these contaminants in the water are unsurprising. In Bethpage, Grumman, a former producer of military aircraft, has become notoriously associated with 1,4-dioxane contamination causing the town of Bethpage to shut down three wells in 2018 due to a plume (Newsday, 2018).

Limitations

The universe of communities for which we collected data were not heterogeneous. Many of the smaller villages were exponentially wealthier than others likely skewing the data. However, American Fact Finder does not report income levels exceeding $250,000, so there is some measure of control for limiting enormous wealth disparities in our data set. In order to determine whether including these smaller, wealthier villages skewed the data, we randomly selected 24 "control" communities using a random number generator to run a linear regression. We found that there was little difference in the results between the full data set of towns and the 24 randomly selected towns. Additionally, it is important to note that there is a wide difference in levels of contaminants with above standard levels. Some towns had contaminants at, or just above, acceptable levels, while other towns had levels that were exponentially higher.

The most important limitations to our analysis is that well capture zones are interconnected to the water supply. Therefore, it can be difficult to know exactly whether the water in a well was contaminated at or near the well or at source point several miles away. Most of the ASL towns are in close proximity to one another. For example, Garden City and Bethpage are eight miles apart.

It is also difficult to determine whether income is the cause or effect of the impact on water quality in low income areas. Are regions with contamination cheaper to live in, and thus more people with low incomes live there? Or do industries take advantage of low income towns by performing poor or illegal practices with respect to improper handling and disposal of contaminants? Additionally, given that demographic shifts (towns shifting from low income to wealthy) can occur more quickly than contaminants can move or dissipate, it can be difficult to determine if contamination existed prior to or after a demographic group settled in a region. However, the most salient point determined through this research is the description of the current water quality as it exists in these towns. The analyses conducted here clearly show that residents in low income towns experience more ASL of contaminants in their untreated water. As previously noted, environmental clean-up sites do occur more often in low income regions. In fact, 70 percent of contaminated areas are located near low-income housing across the U.S. (EPA, 2017a). Contamination can also be caused by industry, or can exist prior to when the area was settled as in the case of Bethpage and the Grumman company. Despite the disproportionate number of Superfund sites in low income regions as opposed to higher income ones, research has shown that lower income communities that have contamination are less likely to receive funding (and thus placement on the Superfund list) for removal of toxic materials. O'Neill (2007) notes that the EPA has been less responsive to minority communities with respect to placing contaminated areas on the Superfund site (thus allowing for funding of clean) than they have been to wealthier and whiter communities. One may infer from these findings that there are even a greater number of low income communities living among contamination than officially reported, particularly in comparison to higher income communities.

Another significant impact that untreated water has on a region is the cost of treatment. If indeed residents in lower income regions live in areas with higher levels of contaminants in their untreated water, the cost of treating this water may be passed on to them. The economic implications are mostly borne by the water authorities or districts that manage the treatment of water, and therefore the rate payer.

Conclusion

Future research should continue to exam data beyond the present three years that were available. Research also is needed on the health impacts of exposure to environmental clean-up sites overall, even after water has been treated. Additionally, an extension of this research would include mapping the source of contamination to the well in which it is found to better make inferences about the communities that are impacted. While this study is regional, these methods may be duplicated on a national level in order to better identify patterns income disparity and contamination and water quality. A conversation is warranted that compares the disparities in water quality across nations, their causes and efforts for equal access to remediation.

References

American Fact Finder. 2018. [online]. Available at: https://factfinder.census.gov

Balazs, C. L.; Morello-Frosch, R.; Hubbard, A. E.; Ray, I. 2012. Environmental justice implications of arsenic contamination in California's San Joaquin Valley: A cross-sectional, cluster-design examining exposure and compliance in community drinking water systems. *Environmental Health: A Global Access Science Source,* 11, 84-95 https://doi.org/10.1186/1476-069X-11-84

Brown, C. J.; Schoonen, M. A. A. 2003. The origin of high sulfate concentrations in a coastal plain aquifer, Long Island, New York. *Applied Geochemistry,* 19 (3), 343-358. https://doi.org/10.1016/S0883-2927(03)00154-9

Calderon, R. L.; Johnson, C.; Craun, Gunther, F.; Dufour, A.; P, Karlin, R. J.; Sinks, T.; Valentine, J. L. 1993. Health risks from contaminated water: do class and race matter? *Toxicology and Industrial Health,* 9(5), 879-900. https://doi.org/10.1177/074823379300900510

Eckhardt, D. A.; Stackleberg, P. E. 1995. Relation of groundwater quality to land use on Long Island, New York. *Ground Water*, 33(6), 1019–1033. https://doi.org/10.1111/j.1745-6584.1995.tb00047.x

Environmental Protection Agency. 2016. *Chemical and Toxics Topics* [online], [cited 25 June 2019]. Available at: https://www.epa.gov/environmental-topics/chemicals-and-toxics-topics

Environmental Protection Agency. 2017a. *Population surrounding 1,836 superfund remedial sites* [online], [cited 25 June 2019]. Available at: https://www.epa.gov/sites/production/files/2015-09/documents/webpopulationrsuperfundsites9.28.15.pdf

Environmental Protection Agency. 2018. *Determining the prevalence of contaminants in treated and untreated drinking water* [online], [cited 21 June 2018]. Available at: https://www.epa.gov/water-research/determining-prevalence-contaminants-treated-and-untreated-drinking-water

Farzin, Y. H.; Grogan, K. A. 2013. Socioeconomic factors and water quality in California. *Environmental Economics and Policy Studies,* 15(1), 1-37. https://doi.org/10.1007/s10018-012-0040-8

Flanagan, S. V.; Spayd, S. E.; Procopio, N. A.; Chillrud, S. N.; Ross, J.; Braman, S.; Zheng, Y. 2016. Arsenic in private well water part 2 of 3: Who benefits the most from traditional testing promotion? *Science of The Total Environment,* 562, 1010-1018. https://doi.org/10.1016/j.scitotenv.2016.03.199

Long Island Commission on Aquifer Protection. 2017. *Watertraq* [online], [cited 30 November 2017]. Available at: http://liaquifercommission.com/watertraq.html

Newsday. 2017. *Environmental cleanup sites on Long Island* [online], [cited 13 July 2018]. Available at: https://projects.newsday.com/databases/long-island/environmental-cleanup-sites/

Newsday. 2018. *Bethpage water district to shut three wells sites over well concerns* [online], [cited 25 June 2019]. Available at: https://www.newsday.com/long-island/nassau/bethpage-plume-wells-1.18465891

O'Neill, S. G. 2007. Superfund: Evaluating the impact of executive order 12898. *Environmental Health Perspectives,* 115, 1087-1093. https://doi.org/10.1289/ehp.9903

Ross, D. 2017. Why the EPA is allowing contaminated groundwater to go untreated; Letting contaminants slowly diminish over time saves money for polluters, but could jeopardize drinking water supplies and cost taxpayers dearly. *Newsweek,* 10 [online], [cited 13 July 2018]. Available at: https://www.newsweek.com/2017/03/17/toxic-waste-contaminated-water-monitored-natural-attenuation-epa-565830.html

Sherwin, B. D. 2017. Pride and prejudice and administrative zombies: How economic woes, outdated environmental regulations, and state exceptionalism failed Flint, Michigan. *University of Colorado Law Review,* 88 (3) [online], [cited 13 July 2018]. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2759015

Smith, T.; Krometis, L. H.; Hagedorn, C.; Lawrence, A.H.; Benham, B.; Ling, E.; Ziegler, P.; Marmagas, S. W. 2014. Associations between fecal indicator bacteria prevalence and demographic data in private water supplies in Virginia. *Journal of Water and Health,* 12(4), 824-834. https://doi.org/10.2166/wh.2014.026

Squillace, P. J; Moran M. J.; Lapham W. W.; Price C. V.; Clawges, R. M; Zogorski J. S. 1999. Volatile organic compounds in untreated ambient groundwater of the

United States, 1985-1995. *Environmental Science &Technology*, 33, 23, 4176-4187. https://doi.org/10.1021/es990234m

VanDerslice J. 2011. Drinking water infrastructure and environmental disparities: Evidence and methodological considerations. *American Journal of Public Health*, 101. S109-S114. https://doi.org/10.2105/AJPH.2011.300189

Watson, E.B.; Powell, E.; Maher, N.P.; Oczkowski, A.J.; Paudel, B.; Starke, A.; Szura, K; Wigand, C. 2018. Indicators of nutrient pollution in Long Island, New York, estuarine environments. *Marine Environmental Research*, 134, 109-120. https://doi.org/10.1016/j.marenvres.2018.01.003