ENVIRONMENTAL HAZARD EXPOSURE DISPARITIES IN SACRAMENTO COUNTY

A Thesis

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by

Margaret Irene Taylor

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by

Margaret Irene Taylor

Approved by:

__________________________________, Committee Chair
Susanna Curry, PhD

__________________________________, Second Reader
Arturo Baiocchi, PhD

____

Date

Student: Margaret Irene Taylor

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Serge Lee, PhD   Date

Division of Social Work

Abstract

of

ENVIRONMENTAL HAZARD EXPOSURE DISPARITIES IN SACRAMENTO COUNTY

by

Margaret Irene Taylor

Exposure to environmental hazards and pollution leads to deleterious health outcomes, and low-income and communities of color are disproportionately burdened. The present study utilizes the publicly available dataset "CalEnviroScreen3.0" to conduct a quantitative analysis of socioeconomic predictors of pollution burden in Sacramento County to better-inform local environmental justice efforts. Even when controlling for other socioeconomic variables, poverty most significantly predicted pollution burden (b=0.27, $p < .001$). Social workers should help initiate interdisciplinary collaboration and advocate for low-income communities to decrease disproportionate exposure to pollution and resulting negative health outcomes.

_______________________, Committee Chair
Susanna Curry, PhD

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Date

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Chapter 1

INTRODUCTION

"Place" matters to health because the locations in which people live shape their behaviors, health choices, and access to medical care (Haley et al., 2012). Health varies sharply by geography because unhealthful conditions are concentrated in disadvantaged areas, thus restricting many low income and communities of color from leading healthful lives (Haley et al., 2012). One such unhealthful condition is the presence of pollution and other man-made environmental hazards.

Pollution of air, water, soil, chemical pollutants, and occupational pollutants is the primary environmental cause of poor health outcomes (Jeremy, 2017). In 2015, pollution was responsible for roughly 16% of all global deaths (Jeremy, 2017). In particular, sustained exposure to air pollution has been linked to respiratory and neurological health issues (i.e. strokes) and is likely linked to other various disorders of the nervous system (Jeremy, 2017). The term "environmental hazard" is used to encompass various man-made and natural disasters, including pollution of all kinds. In this thesis, "environmental hazard" refers to man-made environmental hazards such as toxic emissions from industrial sites, automobile emissions, agricultural pollution from pesticides, and others (Haley, Broaddus, Zimmerman, Woolf, & Evans, 2012). Decision-making processes allow companies and institutions to create environmental hazards, contributing to poor health outcomes – especially among Low-income and people of color (Haley et al., 2012).

There are complex and pervasive barriers in environmental decision-making due to social, political, and economic forces and therefore varying approaches to environmental advocacy and preservation. “Environmentalism” seeks to preserve natural biodiversity and ecosystems, and the field is historically dominated by affluent white people (Philip & Reisch, 2015). Though environmentalism movements have done much to promote positive environmental policies, they do little to address disparities in exposure to environmental hazards and their subsequent impact on communities of color and low-income communities. “Environmental justice,” on the other hand, considers the experiences of populations which are most affected by environmental degradation and hazards; they then enhance communities’ ability to participate in or lead decision-making which inevitably shapes their exposure to life-threatening health hazards (Philip & Reisch, 2015). Given social workers’ mission to advance human rights and amplify the voices of historically marginalized populations, it makes sense for them to be more involved in environmental justice movements. “Green social work” is an attempt at this participation which emphasizes the importance of dismantling structural inequalities which lead to disproportionate environmental harm in low-income and minority communities (Philip & Reisch, 2015). However, it is not particularly well-spread or woven into the fabric of the social work profession and approach. A more thorough review and summary presented in Chapter 2 supports the notion that social workers can be effective in advancing environmental justice.

Environmental hazards are not equally spread across cities, communities, or neighborhoods and therefore the negative effects are not spread equally across the population. Toxic waste facilities are often located in low-income neighborhoods or communities of color due to historical, sociopolitical, and economic processes (Brender, Maantay, & Chakraborty, 2011; Pais, Crowder, & Downey, 2014; Landrine & Corrall, 2014). This disparate exposure leads to disproportionate deleterious health conditions in low income and communities of color (Haley, Broaddus, Zimmerman, Woolf, & Evans, 2012; Philip & Reisch, 2015; Brender et al., 2011; Milstein, Homer, Briss, Burton, & Pechachek, 2011; Pascal, Pascal, Bidondo, Cochet, Sarter, Stempfelet, & Wager, 2013). Stricter environmental regulations might protect against toxic exposures, but the barriers to environmental protection are robust; they require advocacy to local governments and efforts to rewrite policies which afford corporations the right to site their facilities (Mohai & Saha, 2015).

The research literature frames environmental hazard exposure as harmful to individual and population health, but there are gaps in the measurement of incidences and explanations for disparate pollution burden in low-income and communities of color. A more thorough discussion of research gaps follows in chapter two. The present study seeks to identify communities in Sacramento County which are disproportionately burdened by environmental hazards, to analyze whether demographic factors predict exposure, and to highlight the need for social workers in environmental justice advocacy.

Research Questions and Hypotheses

In this study, I will investigate three research questions: 1) What is the average pollution burden and socioeconomic make-up for communities within Sacramento County, 2) Are socioeconomic factors significantly correlated with pollution burden and each other, and 3) Do socioeconomic factors (poverty, housing burden, linguistic isolation, unemployment, education) predict pollution burden. I have two hypotheses, listed below.

H_1: There will be a statistically significant positive *relationship* between socioeconomic factors and pollution burden, and between all socioeconomic factors.

H_2: There will be a significant *prediction* of pollution burden by poverty, unemployment, housing burden, low educational attainment, and linguistic isolation.

Chapter 2

LITERATURE REVIEW

Environmental justice is a relatively contemporary research topic. During the late 1970s and 1980s, communities of color and environmental justice advocates across the United States began publicly asserting their disproportionate vulnerability to the deleterious effects of environmental hazards (United States Commission on Civil Rights, 2003). In the nation's first environmental justice court case (Bean v. Southwestern Waste Management Corporation, 1979), residents of a neighborhood in Houston, Texas alleged that the decision to site a garbage dump in their community would cause irreparable harm and was racially motivated, thus violating their civil rights (U.S. Commission on Civil Rights, 2003). Unable to provide sufficient evidence demonstrating a pattern of intentional siting of waste facilities in communities of color, residents lost, and the garbage dump was built (U.S. Commission on Civil Rights, 2003). This case highlighted that communities affected by environmental risks need increased access to information – including formal data collection.

In 1983, the General Accounting Office (GAO) published one of the first studies focusing on disproportionate environmental risk distribution; in 1987, the United Church of Christ published a similar and more comprehensive national study (U.S. Commission on Civil Rights, 2003). Both studies confirmed environmental justice advocates' assertions that people with low-income and racial minorities face increased risk of environmental hazard exposure (U.S. Commission on Civil Rights, 2003). The studies also established income as a determining factor in risk exposure, though race was deemed the stronger predictor (U.S. Commission on Civil Rights, 2003).

The present study builds upon literature investigating whether man-made environmental hazards disproportionately affect marginalized communities in Sacramento County and whether the social work profession is well-equipped for involvement in local environmental efforts. The following chapter reviews current research literature regarding the health effects of exposure to environmental hazards, evidence for disproportionate presence of environmental hazards in low-income communities and communities of color, theories and explanations for disparate siting, and effective or potentially effective methodologies to study and decrease disparities in environmental hazard exposure. Finally, gaps in the research literature are identified along with suggestions for future research directions.

Most articles were found through a search on One Search: “environmental racism” OR “environmental justice” AND “health disparities.” There were 416 results. The author chose roughly 10 relevant articles from this search and subsequently drew sources from the articles’ citations. The author compiled a list of roughly 60 relevant articles and reviewed each article. The list was then reduced to 39 articles and identified as relevant to one of five main sections within the topic and literature review: introduction and overview of topic, articles explaining causes of disparate siting, articles describing the health effects of exposure to environmental hazards, articles detailing racial and socioeconomic health disparities resulting from disparate exposure, and articles outlining environmental justice movements or techniques to address such disparities.

Health Effects of Exposure to Environmental Hazards

Geographic proximity to hazardous material disposal facilities, industrial sites and factories, pesticide-laden farms, highways or busy streets, and other sources of potent emissions is related to an increase in adverse physical and psychosocial health outcomes. A plethora of national studies find a significant relationship between exposure to environmental hazards and adverse physical health outcomes including asthma and other respiratory problems (Haley et al., 2012; Marques & Lima, 2011; Brender et al., 2011; Cohen, Lopez, Malloy, & Morello-Frosch, 2012), cancers (Brender et al., 2011; Morello-Frosch, Woodruff, Axelrad, & Caldwell, 2000; Pascal et al., 2013), premature mortality (Brender et al., 2011; Takeuchi, Walton, & Leung, 2010; Pascal et al., 2013; Haley et al., 2012), and cardiovascular problems (Brender et al., 2011; Pascal et al., 2013; Orban, McDonald, & Sutcliffe et al., 2016).

The effect of environmental hazards on mental health has been studied less frequently, but researchers still find relationships between exposure to hazards and increased anxiety (Couch & Coles, 2011; Orban et al., 2016; Marques & Lima, 2011; Santiago, Wadsworth, & Stump, 2011), depressive symptoms (Couch & Coles, 2011; Orban et al., 2016; Marques & Lima, 2011; Santiago et al., 2011), insomnia (Orban et al., 2016) and decreased emotional coping skills (Couch & Coles, 2011; Kemp & Palinkas, 2015) in individuals. An important research finding is that while it is difficult to demonstrate a direct relationship between environmental hazard exposure and mental health disorders, it directly causes community and individual psychosocial stress, which can increase prevalence of both mental and physical health conditions (Couch & Coles, 2011, Santiago et al., 2011, Orban et al., 2016, Haley et al., 2012, Allacchi & Magder, 2013, Brender et al., 2011 , Kemp & Palinkas, 2015, Gee & Payne-Struges, 2004).

Evidence of Disparate Exposure and Subsequent Health Impacts in Low Income and Communities of Color

Low income and communities of color experience disproportionate exposure to environmental hazards and suffer from increased stress and other poor physical and mental health outcomes. The first national study to examine the relationship between toxic waste facilities and race took place in 1982. The researchers demonstrated racial and ethnic exposure disparities even when controlling for socioeconomic status, but socioeconomic status was the second most significant predictor for communities exposed to disproportionate environmental exposure (Chavis & Lee, 1987). More contemporary researchers have found similar results consistently since Chavis and Lee's landmark study, published in 1987.

Community-level capabilities to cope with stressors fall into the social and cultural arenas; they can be conceptualized as "social capital" and "collective efficacy," respectively. Social capital refers to the state of entities within a neighborhood or community, all characterized by a degree of social structure and ability to facilitate individual actions within said structure (Couch & Coles, 2011). It is measured using various community-level indicators: income, housing, employment, crime, and types of family structures (Couch & Coles, 2011). Collective efficacy, rather, refers to a community's belief that social capital can be used for collective good, and it is measured more subjectively through observation and surveys (Couch & Coles, 2011). Social capital and collective efficacy address matters of control and powerlessness, and both are correlated negatively with community-level stress and positively with community members' health (Couch & Coles, 2011). When chronic environmental hazards are present in disadvantaged communities already experiencing psychosocial stressors (low income, high unemployment, discrimination, violence, and crime), it may result in stress proliferation, and an even stronger adverse impact on stress and health (Couch & Coles, 2011; Gee & Payne-Struges, 2004).

A plethora of studies which combine longitudinal demographic data with geocoded data of hazardous site placement demonstrate that low-income communities and communities of color experience disproportionate and persistent exposure to multiple contaminants (Haley et al., 2012; Allacchi & Magder, 2013; Brender et al., 2011; Pais et al., 2014; Downey & Hawkins, 2008; Ash, Boyce, Chang, & Scharber, 2013; Lievanos, 2017; Mohai & Saha, 2007; Crowder & Downey, 2010). According to these studies, differential exposure exists regardless of socioeconomic status or educational level, though those are also significantly related to hazard exposure. Consequently, low-income communities and communities of color experience increased adverse health outcomes from both physical stressors and contamination-related psychosocial stress and mental health problems (Couch & Coles, 2011).

Explanations for Disparate Siting of Pollution Sources

Some researchers assert that demographic changes after the siting of toxic facilities have led to disproportionately high concentrations of low-income and communities of color around hazardous sites. National-level studies to assess disparate siting have historically used research methodologies which underestimate the severity of exposure disparity (Mohai & Saha, 2015; Mohai & Saha, 2015). Recent studies, however, utilize research methods which clarify the severity and driving forces of disparate siting of toxic facilities (Mohai & Saha, 2015; Mohai & Saha, 2015).

Longitudinal studies that utilize areal apportionment methods to measure current-day demographic disparities in areas with facilities which were sited in 1966 and 1970, however, suggest that disparities are a function of both disparate siting at the time of siting and post-siting demographic change (Mohai & Saha, 2015; Mohai & Saha, 2015; Stretesky & McKie, 2016). However, national-level studies utilizing a unit-hazard coincidence measurement system are cross-sectional and thus measure disparities at one point in time; these studies tend to report modest racial and socioeconomic disparities in hazard exposure and disparities at time of siting and post-siting demographic change are found to be virtually non-existent (Mohai & Saha, 2015; Mohai & Saha, 2015; Stretesky & McKie, 2016).

Socio-political and economic explanations, also known as “path of least resistance” explanations, are used to explain the disparate siting of toxic facilities in low income communities and communities of color. According to these explanations, corporations face fewer restrictions, fewer financial consequences, and less community resistance in low-income communities and therefore often site facilities in and around those communities (Mohai & Saha, 2015). The communities often have social isolation and limited political power to resist unwanted land use decisions by governments and corporations (Haley et al., 2012; Ash et al., 2013; Kremer, 2016; Zwartveen & Boelens, 2014). This happens frequently enough that researchers coined an acronym, “LULUs,” to indicate “locally unwanted land uses.” Per “path of least resistance” explanations, corporations deliberately target communities with limited political clout and therefore limited likelihood to successfully thwart new toxic facility siting proposals.

However, these explanations do not explicitly account for environmental racism and the historical processes which have deliberately decreased the political power and economic viability of communities of color. The racial discrimination hypothesis posits that toxic facilities are placed in communities of color as a direct effect of government-endorsed racial discrimination (Mohai & Saha, 2015; Mohai & Saha, 2015). In Chavis and Lee’s landmark environmental justice study in 1987, researchers conducted two cross-sectional studies building upon investigations and challenges toward the overwhelming presence of toxic substances in residential areas across the country. They conducted their studies to examine the relationship between treatment, storage, and disposal of hazardous wastes in relation to race. Their results showed that race was the most significant role in the location of commercial hazardous wastes across the country, even after controlling for urbanization and regional differences (Chavis & Lee, 1987). In more recent studies, many researchers have found in national-level studies that communities of color are disproportionately exposed to environmental toxins even after controlling for socioeconomic status and income (Chavis & Lee, 1987; Mohai & Saha, 2007; Chitewere, Shim, Barker, & Yen, 2017; Gee & Payne-Struges, 2004; Pulido, 2000; Mohai & Saha, 2015; Mohai & Saha, 2015).

Commonly cited methodological weaknesses in studies of disparate exposure include utilization of cross-sectional, unit-hazard coincidence methods which do not account for historical neighborhood demographic changes and vastly underestimate the degree of racial and sociopolitical disparities (Mohai & Saha, 2015; Mohai & Saha, 2015). Researchers assert that more consistent usage of distance-based and longitudinal methods will provide a more accurate assessment of disparate exposure to harmful environmental toxins and subsequent health disparities (Mohai & Saha, 2015; Mohai & Saha, 2015).

Best Practices Proposed to Advance Environmental Justice

Research demonstrates sufficient evidence of disproportionate adverse health outcomes from environmental hazards in low income and communities of color to warrant government action to protect people from the hazards and their harmful effects (Brender et al., 2011). Researchers assert that the government should consider the findings of disparate environmental hazard impacts when siting and approving environmentally burdensome facilities and land uses, regulating and enforcing environmental efforts concerning pollution, and in promoting environmental health justice (Brender et al., 2011). However, low income and communities of color largely lack the necessary technical environmental knowledge and political clout to advocate for just governmental practices and regulations (Couch & Coles, 2011; Philip & Reisch, 2015). The field of environmental justice is relatively small but growing steadily, and several researchers have reported on successful environmental justice efforts that can be built upon (Philip & Reisch, 2015; Kemp, 2011; Finley-Brook & Holloman, 2016; Giugni & Grasso, 2015; Pulido, 2000).

Several researchers propose that accurate risk assessment procedures before siting could help to deter placement of hazardous facilities or sites in low income and communities of color. Researchers assert that risk assessments should utilize research methodologies (like those listed above) which are longitudinal, and in which geocoded data paints a clear picture of areas with disproportionate hazard exposure based on race and socioeconomic status (Mohai & Saha, 2007; Mohai & Saha, 2015; Mohai & Saha, 2015). Environmental justice researchers also advocate for utilization of local communities' knowledge to produce more comprehensive and culturally-responsive risk assessments – a process referred to as community-based participatory research (Couch & Coles, 2011; Philip & Reisch, 2015; Allacchi & Magder, 2013; Pascal et al., 2013; Mohai & Saha, 2007; Kemp & Palinkas, 2015; Cohen et al., 2012). To many researchers, interdisciplinary collaboration between environmental advocates, corporations, politicians, and local communities and subsequently increased cultural knowledge is essential to environmental justice movements (Couch & Coles, 2011; Philip & Reisch, 2015; Messer, Shriver, & Adams, 2015; Allacchi & Magder, 2013; Zwartveen & Boelens, 2014; Kemp & Palinkas, 2015; Kemp, 2011; Cohen et al., 2012; Finley-Brook & Holloman, 2016; Giugni & Grasso, 2015; Gee & Payne-Struges, 2004; Pulido, 2000).

Social workers can fulfill the role of advocate and interdisciplinary link between politicians and communities with few resources and they have been successful in doing so in several case studies (Philip & Reisch, 2015; Kemp & Palinkas, 2015; Kemp, 2011).

Given the complex nature of racism and its impact on hazard exposure, research into the historical and structural processes which reinforce racism are needed. Social work's emphasis on human rights and social justice can be utilized to increase environmental justice (Philip & Reisch, 2015; Kemp & Palinkas, 2015; Kemp, 2011).

Research Gaps and Future Directions

The research literature frames environmental hazard exposure as harmful to individual and population health. Differing research methodologies, however, produce contradictory incidences and explanations for disparate spatial dispersion of hazards in low-income and communities of color (Mohai & Saha, 2015; Mohai & Saha, 2015). Evidently, social work values align with environmental justice efforts and warrant increased participation therein (Philip & Reisch, 2015; Kemp, 2011). In order to do so, however, hazard exposure disparities must be calculated more accurately. Research suggests that incorporating local, community knowledge and bridging gaps across academia, politics, business, and social work could be largely beneficial to environmental justice efforts (Philip & Reisch, 2015; Messer et al., 2015; Allacchi & Magder, 2013; Mohai & Saha, 2007; Kemp & Palinkas, 2015; Kemp, 2011). Using existing quantitative data and community-based research initiatives could paint a clearer picture of disparities, allowing for appropriately-targeted advocacy initiatives (Philip & Reisch, 2015; Kemp, 2011; Messer et al., 2015; Allacchi & Magder, 2013). The present study attempts to identify areas and communities in Sacramento which have disproportionate exposure to hazards and analyze whether community demographic characteristics predict exposure to pollution. Accordingly, environmental justice researchers and advocates can better-direct their community-based efforts.

Chapter 3

DATA & METHODS

Data Source and Sample

The purpose of the present study is to determine whether socioeconomic factors predict pollution burden in Sacramento communities. With this information, environmental justice advocates can determine where advocacy and resources are needed to ameliorate the damaging health impacts of pollution. The present study explores three research questions: 1) What is the average pollution burden and socioeconomic make-up for communities within Sacramento County, 2) Are socioeconomic factors significantly correlated with pollution burden and each other, and 3) Do socioeconomic factors (poverty, housing burden, linguistic isolation, unemployment, education) predict pollution burden.

The goal of this research study is to use quantitative data describing the spatial distribution of cumulative environmental hazard impacts in Sacramento County to understand how socioeconomic characteristics predict disproportionate exposure to environmental toxins. Secondary data was retrieved from the latest version of the California Communities Environmental Health Screening Tool - CalEnviroScreen 3.0 (hereafter CalEnviroScreen) - including environmental, health, and socioeconomic information for 8,035 California census tracts. The analysis in the present study was limited to census tracts within Sacramento County (n = 317).

CalEnviroScreen

The dataset is compiled by the California Environmental Protection Agency (CalEPA) and the Office of Environmental Health Hazard Assessment (OEHHA) with the ultimate purpose of informing state and federal resource allocation to advance environmental justice in disadvantaged California communities (Rodriguez & Zeise, 2017). This screening tool was developed in part to determine which communities should receive funds generated by the California Global Warming Solutions Act of 2006 and its carbon auctions (Rodriguez & Zeise, 2017). Senate Bill 535, created in response to the 2006 act, dictates that the California Environmental Protection Agency (CalEPA) identify disadvantaged communities in California and allocate at least 25% of proceeds generated by the 2006 act to those disadvantaged communities (Rodriguez & Zeise, 2017). See Appendix 1 for a description of CalEnviroScreen's method and more information regarding each individual indicator. In my analysis, I am interested specifically in socioeconomic factors as predictors for pollution burden. I describe each of my specific variables below.

Dependent Variable

Pollution Burden

The dependent variable "Pollution Burden" was provided by CalEnviroScreen. The measure of burden was calculated as follows: scores on individual indicators within two "components" were averaged to create a score. The two components are "exposure" (i.e., particulate matter concentrations) and "environmental effects" (i.e., presence of toxic waste facilities). To calculate "pollution burden," exposure and environmental effects scores were averaged. The resulting average is the pollution burden percentile (Rodriguez & Zeise, 2017). Environmental effects is given a half weighting because the indicators reflect the presence of a potential hazard, rather than exposure to that hazard (Rodriguez & Zeise, 2017). See Appendix 1 for more information about indicators included within "pollution burden". The resulting "pollution burden" percentile for each census tract is a scale variable. Percentiles indicate a census tract's pollution burden relative to other census tracts in California. The range of pollution burden percentiles is from 0.97% - 95.07%. The mean of pollution burden is 34.76 and the standard deviation is 22.79.

Independent Variables

Educational Attainment

Research indicates that low educational attainment is associated with increased vulnerability to the negative health effects of environmental hazard exposure, and will therefore be included in the analysis (Rodriguez & Zeise, 2017). Within the CalEnviroScreen data education is extracted from the 2011-2015 American Community Survey, which reports the percentage of residents within a California census tract who are over the age of 25 and with a high school education or higher (Rodriguez & Zeise, 2017). This percentage was then subtracted from 100; the result reflects the percentage of the population whose educational attainment is less than high school-level (Rodriguez & Zeise, 2017). Some census tracts received unreliable estimates and therefore did not receive a score for the educational attainment indicator. A more detailed discussion of the limitations of each indicator to follow in chapter five. Census tracts were put in order of their percentage of population “over 25 with less than a high school education.” Each census tract was then assigned a percentile which reflects its education level relative to other tracts (Rodriguez & Zeise, 2017). The range of percentiles is 0% - 93.12%. The mean is 41.92 and the standard deviation is 22.82.

Housing Burden

This analysis also takes into account the proportion of housing-burdened low-income households within each census tract. The indicator for each census tract is the percent of households that are both “low-income” (making less than 80% of the Area Median Family Income as established by the US Department of Housing and Urban Development (HUD)) and severely burdened by housing costs (paying 50% or more of their income to housing costs) (Rodriguez & Zeise, 2017). Census tracts were ordered by their indicated percentage on these measures, and then assigned a percentile score based on their relative rank across all census tracts in California. Census tracts with unavailable housing data were excluded from analysis, and the total n for census tracts in Sacramento County was 312. The range of percentiles was between .05% - 99.67%. The mean for Sacramento County was 46.08 and the standard deviation was 28.23.

Linguistic Isolation

Another independent variable included in the analysis reflects the proportion of limited English-speaking households within each census tract during years 2011-2015 (Rodriguez & Zeise, 2017). Census tracts were ordered by their percentage; each census tract was then assigned a percentile based on the distribution of percentages across all census tracts which met criteria for inclusion. The n for linguistic isolation is 307. The range of percentiles is 0% - 97.32%. The mean is 40.08 and the standard deviation is 24.90.

Poverty

This independent variable reflects a census tract's proportion of households living in poverty relative to other census tracts. The indicator for each census tract is its percentage of the population living below two times the federal poverty level during years 2011-2015 (Rodriguez & Zeise, 2017). Census tracts were ordered by their percentage; each census tract was then assigned a percentile based on the distribution of percentages across all census tracts which met criteria for inclusion. The n for poverty is 315. The range of percentiles is 0.13% - 99.84%. The mean is 53.43 and the standard deviation is 26.14.

Unemployment

This independent variable reflects a census tract's unemployment rate relative to other census tracts. The indicator for each census tract is its percentage of the population over 16 years of age that is both unemployed and eligible for the labor force during years 2011-2015 (Rodriguez & Zeise, 2017). Student citizens, retired persons, homemakers, people who are institutionalized (not including prisoners), persons in the military on active duty, and people who are not looking for work were excluded from this calculation (Rodriguez & Zeise, 2017). Census tracts were ordered by their percentage; each census tract was then assigned a percentile based on the distribution of percentages across all census tracts which met criteria for inclusion. The n for unemployment is 314. The range of percentiles is 99.55 (0.44% - 99.99%). The mean is 61.08 and the standard deviation is 27.98.

Table 1

Descriptive Statistics

Variables	*N*	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Dependent					
Pollution Burden	317	0.97	95.07	34.76	22.79
Independent					
Educational Attainment	315	0.00	93.12	41.92	22.82
Linguistic Isolation	307	0.00	97.32	40.08	24.91
Poverty	315	0.01	99.84	53.43	26.14
Unemployment	314	0.44	99.99	61.08	27.98
Housing Burden	312	0.05	99.67	46.08	28.23

Analysis

To assess the relationships between Pollution Burden and these various socioeconomic factors in Sacramento County my analysis is structured in three phases. The first phase was exploratory and descriptive; I explored the incidence of socioeconomic hardship in communities affected by pollution (and, more broadly, environmental hazards) in Sacramento County. I also identified the mean magnitude of pollution burden and socioeconomic hardship. In the second phase, I conducted a bivariate analysis using Pearson Product-Moment Correlation (Pearson Correlation) to measure whether variables are related to one another. In the third phase, I conducted a multivariate analysis (multiple linear regression) to examine how these social and economic factors function as independent covariates of environmental toxin exposure in the county. Some census tracts contained missing data on certain socioeconomic factors; in the multivariate regression, listwise deletion was performed such that only cases with full data for each independent variable were included in the analysis. Linguistic isolation was excluded from Phase 3 of the analysis because its missing values reduced the sample too drastically with listwise deletion, and the unemployment and housing burden variables were not included in the same regression models to reduce multicollinearity bias. Four linear regression models were analyzed and results for all phases are detailed in the following chapter. I intend to use this study to inform multidisciplinary stakeholders in Sacramento County of the specific geographic locations – and communities – at most risk of exposure to pollution. The specific hypotheses to be analyzed are listed below.

H_1: There will be statistically significant positive relationships between socioeconomic hardships and pollution burden, including:

$H_{1\text{-}A}$: There will be a positive relationship between pollution burden and *poverty.*

$H_{1\text{-}B}$: There will be a positive relationship between pollution burden and *educational attainment*.

$H_{1\text{-}C}$: There will be a positive relationship between pollution burden and *housing burden*.

$H_{1\text{-}D}$: There will be a positive relationship between pollution burden and *unemployment*.

$H_{1\text{-}E}$: There will be a positive relationship between pollution burden and *linguistic isolation*.

H_2: There will be a significant prediction of pollution burden by poverty, unemployment, housing burden, low educational attainment, and linguistic isolation.

$H_{2\text{-}A}$: In the presence of the others, pollution burden is significantly predicted by relative levels of poverty.

$H_{2\text{-}B}$: In the presence of the others, is significantly predicted by relative levels of unemployment.

$H_{2\text{-}C}$: In the presence of the others, is significantly predicted by relative levels of housing burden.

$H_{2\text{-}D}$: In the presence of the others, is significantly predicted by relative levels of educational attainment.

$H_{2\text{-}E}$: In the presence of the others, is significantly predicted by relative levels of educational attainment.

Chapter 4

FINDINGS

In this chapter I present findings from the three phases of analysis used to test my hypotheses. In the first phase of analysis, I explore the frequency and magnitude of pollution burden and socioeconomic factors in census tracts within Sacramento County by calculating frequencies and averages. In the second phase, I assess the bivariate correlations between pollution burden and socioeconomic factors, as well as the correlation between different socioeconomic factors. Specifically, Phase 2 assesses the first set of hypotheses listed below.

$H_{1\text{-}A}$: There will be a positive relationship between pollution burden and *poverty.*

$H_{1\text{-}B}$: There will be a positive relationship between pollution burden and *educational attainment*.

$H_{1\text{-}C}$: There will be a positive relationship between pollution burden and *housing burden*.

$H_{1\text{-}D}$: There will be a positive relationship between pollution burden and *unemployment*.

$H_{1\text{-}E}$: There will be a positive relationship between pollution burden and *linguistic isolation*.

In the third and final phase, I assess how socioeconomic factors function as independent covariates of pollution burden. Specifically, I assess the second set of hypotheses, listed below.

H_2: There will be a significant prediction of pollution burden by poverty, unemployment, housing burden, low educational attainment, and linguistic isolation.

$H_{2\text{-}A}$: In the presence of the others, pollution burden is significantly predicted by relative levels of poverty.

$H_{2\text{-}B}$: In the presence of the others, is significantly predicted by relative levels of unemployment.

$H_{2\text{-}C}$: In the presence of the others, is significantly predicted by relative levels of housing burden.

$H_{2\text{-}D}$: In the presence of the others, is significantly predicted by relative levels of educational attainment.

$H_{2\text{-}E}$: In the presence of the others, is significantly predicted by relative levels of educational attainment.

Phase 1: Univariate Analysis

In phase one of the analysis, I calculated the frequencies and descriptive statistics for each variable in Sacramento County census tracts to answer my first research question: what is the prevalence of pollution burden and socioeconomic hardships in Sacramento County?

Table 2

N, Minimum and Maximum Values, Mean, and Standard Deviation of Variables

Variables	*N*	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Dependent					
Pollution Burden	317	0.97	95.07	34.76	22.79
Independent					
Educational Attainment	315	0.00	93.12	41.92	22.82
Linguistic Isolation	307	0.00	97.32	40.08	24.91
Poverty	315	0.01	99.84	53.43	26.14
Unemployment	314	0.44	99.99	61.08	27.98
Housing Burden	312	0.05	99.67	46.08	28.23

Table 1 (above) shows the N, minimum value, maximum value, mean, and standard deviation for each variable. The mean pollution burden percentile was 34.76 (N = 317). The mean educational attainment percentile was 41.92 (N = 315). When looking closer at the data, 13% of the population within Sacramento census tracts, on average, has less than a high school education. The mean linguistic isolation percentile was 40.08 (N = 307). On average, 7% of households within Sacramento census tracts are limited English-speaking. The mean poverty percentile was 53.43 (N = 315). The average percentage of households two times below the poverty level in Sacramento County census tracts is roughly 38%. The mean unemployment percentile was 61.08 (N = 314). The average percentage of unemployed persons in Sacramento County census tracts is 12%. The mean housing burden percentile was 46.08 (N = 312). The average percentage of low-income households who are severely burdened by housing costs is 18%. Each variable contained cases scoring below the first percentile and over the 93rd percentile (See Table 1).

Phase 2: Bivariate Analysis

In phase two of the analysis, I conducted a Pearson's Product-Moment Correlation analysis (Pearson Correlation) to answer my second research question: Are socioeconomic factors significantly correlated with pollution burden and each other?

Table 3

Pearson's Correlation Matrix

	Pollution Burden	Poverty	Education	Housing Burden	Unemployment	Linguistic Isolation
Pollution Burden	1					
Poverty	.316**	1				
Education	.177**	.800**	1			
Housing Burden	.195**	.776**	.609**	1		
Unemployment	.210**	.694**	.596**	.555**	1	
Linguistic Isolation	.144*	.629**	.739**	.488**	.409**	1

**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

As shown in Table 2 (above), results of the Pearson Correlation analysis indicate that poverty and pollution burden have a statistically significant and moderately strong correlation (0.316, $p < 0.05$), and education has a significant and strong correlation with poverty (0.800, $p < 0.01$). All other independent variables have a significant, but weak, positive correlation with pollution burden (see Table 2). Many independent variables are also significantly correlated with one another. Pearson's r values that are roughly 0.1 indicate a weak correlation; scores roughly equal to 0.3 indicate a moderate correlation; and scores greater than or equal to 0.5 indicate a strong correlation.

Phase 3: Multivariate Linear Regression Analysis

In phase three, I conducted a multivariate linear regression analysis to answer my third research question: will socioeconomic factors predict pollution burden in Sacramento County? Table 3 (below) shows the results of four models of the linear regression analysis. Separate regressions were conducted to reduce multicollinearity bias. The first regression model was calculated to predict pollution burden just based on relative poverty, as poverty was revealed as having the strongest bivariate correlation with pollution burden in phase two of the analysis (see Table 2). The first model indicated that relative poverty was significantly predictive of pollution ($b=.27$, $p<.001$); which suggests that pollution burden increased .27 percentile points for each percentile increase of poverty in the area. Overall, the regression model was found to be significant ($F[1, 308) = 32.89$, $p < .001$), with an R2 of .100, which suggests that poverty by itself explains 10% of the variance in pollution rankings.

The second regression model predicted pollution burden based on poverty and education. A significant regression equation was found (F[2, 309) = 19.64, $p < .001$), with an R2 of .11, which increased the amount of variance explained by only 1% compared to the previous model.. The second model nonetheless indicated a stronger effect for poverty (b=.43, p<.001) when controlling for education, which estimated a negative effect (b=-22, p<.001). The standardized betta coefficients of the model suggest that poverty had twice the relative impact on pollution (β=.49) than education (β=-.21). Accordingly, poverty has strong effect on pollution burden, while education seems to mitigate some of these risks.

The third regression model predicts pollution burden based on poverty, education, and housing burden. A significant regression equation was found (F[3, 309) = 13.76, $p < .001$), with an R2 of .12, which increased the amount of variance explained by only 1% compared to the previous model. The third model nonetheless indicated a stronger effect for poverty (b=.51, p<0.001) when controlling for education, which estimated a negative effect (b=-.22, p<0.001) and housing burden, which estimated a negative effect (b=-.10, p<0.001). The standardized betta coefficients of the model suggest that poverty had more than twice the relative impact on pollution (β=.58) than education (β=-.22) and housing burden (β=-.12). Accordingly, poverty has a strong effect on pollution, while education seems to mitigate some of these risks.

The fourth regression model predicts pollution burden based on poverty, education, and unemployment. A significant regression equation was found (F[3, 309) = 13.76, $p < .001$), with an R2 of .12, which increased the amount of variance explained by only 1% compared to the previous model. The fourth model nonetheless indicated a stronger effect for poverty ($b=.43$, $p<0.001$) when controlling for education, which estimated a negative effect ($b=-.22$, $p<0.001$) and unemployment, which estimated a negative, but statistically insignificant, effect ($b=-.002$, $p<0.001$). The standardized betta coefficients of the model suggest that poverty had twice the relative impact on pollution ($\beta=.49$) than education ($\beta=-.22$), and a much greater impact than unemployment ($\beta=-.002$). Accordingly, poverty has a strong effect on pollution, while education seems to mitigate some of these risks.

Table 4

Linear Regressions

	Model 1 N = 315		Model 2 N = 315		Model 3 N = 312		Model 4 N = 314	
Variables	*B (SE)*	*β*	*B (SE)*	*β*	*B (SE)*	*β*	*B (SE)*	*β*
Poverty	0.27** (0.05)	0.31	0.425** (0.08)	0.485	0.508** (0.10)	0.58	0.426** (0.09)	0.49
Education			-0.22* (0.09)	-0.21	-0.22* (0.09)	-0.22	-0.22* (0.09)	-0.22
Housing Burden					-0.1 (0.07)	-0.12		
Unemployment							-0.002 (0.06)	-0.002
Constant	20.25 (2.84)		21.31 (2.85)		21.44 (2.85)		21.35 (3.14)	
R	0.31		0.34		0.35		0.34	
R^2	0.10		0.11		0.12		0.11	
F	32.89		19.642		13.764		13.053	
df	1		2		3		3	
p	0.000		0.000		0.000		0.000	

**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)\

Controlling for other independent variables, poverty was the only independent variable significantly related to pollution burden in census tracts. When controlling for poverty, education may have a negative effect on pollution burden; accordingly, low levels of education may buffer against pollution burden while holding poverty levels constant. Results suggest that poverty, not education, may be driving pollution burden scores.

Chapter 5

DISCUSSION

In this study, I investigated three research questions: 1) What is the average pollution burden and socioeconomic make-up for communities within Sacramento County, 2) Are socioeconomic factors significantly correlated with pollution burden and each other, and 3) Do socioeconomic factors (poverty, housing burden, linguistic isolation, unemployment, education) predict pollution burden. My hypotheses were as follows:

H_1: There will be a statistically significant positive relationship between socioeconomic hardships and pollution burden, and between all socioeconomic factors.

H_2: There will be a significant prediction of pollution burden by poverty, unemployment, housing burden, low educational attainment, and linguistic isolation.

The results allowed me to reject the null hypothesis of H1 because each variable was found to have a significant and positive correlation with pollution burden and each other variable. I failed to fully reject the null hypothesis of H2; although each model was significant, poverty was the only variable found to have a positive relationship with pollution burden, even after controlling for the other variables. Poverty was more predictive of pollution burden than any other socioeconomic factor.

The finding of poverty as a predictor of pollution burden aligns with prior research. In fact, two of the very first national-level inquiries into environmental hazard exposure disparities revealed that low-income people were disproportionately exposed to man-made hazards (U.S. Commission on Civil Rights, 2003; Chavis & Lee, 1987). More recent studies have also confirmed the disproportionate presence of environmental hazards in low-income communities (Haley et al., 2012; Allacchi & Magder, 2013; Brender et al., 2011; Pais et al., 2014; Downey & Hawkins, 2008; Ash, Boyce, Chang, & Scharber, 2013; Lievanos, 2017; Mohai & Saha, 2007; Crowder & Downey, 2010). Interestingly, although these studies confirm that low-income communities suffer from disproportionate exposure, they found race to be the most significant predictor of hazard exposure regardless of socioeconomic status or education level. The present study did not include race as a predictor, in part due to dataset limitations and in part due to interest in the distinct predictive value of each socioeconomic factor on pollution burden.

Educational attainment was positively correlated with pollution burden (.18, $p < 0.001$) and poverty (.80, $p < 0.001$) in the bivariate analysis, but it had a negative effect on pollution burden when controlling for poverty in the three regression models; that is, low levels of education may buffer against pollution while holding poverty levels constant. There is a bivariate positive relationship, but the findings suggest that high poverty areas tend to be associated with low educational attainment, and that it is poverty, not education, driving pollution burden. This finding largely deviates from prior research, which established low education levels as a positive predictor for disproportionate hazard exposure (Haley et al., 2012; Allacchi & Magder, 2013; Brender et al., 2011; Pais et al., 2014; Downey & Hawkins, 2008; Ash, Boyce, Chang, & Scharber, 2013; Lievanos, 2017; Mohai & Saha, 2007; Crowder & Downey, 2010). However, as mentioned, those same studies establish race as a more significant predictor of pollution burden than education levels and socioeconomic status. Perhaps there are areas in Sacramento County comprised of affluent and/or majority-white populations, in which education levels are modest, that are able to buffer against pollution burden. Alternatively, perhaps the measure of educational attainment in CalEnviroScreen is insufficient to accurately capture low educational attainment. Future research analyzing race as a predictor within Sacramento County could help to clarify these findings.

Some explanations for disparate siting in prior research, including sociopolitical and economic explanations (also known as, "path of least resistance"), would help to explain these findings. According to path of least resistance explanations, corporations face fewer restrictions, fewer financial consequences, and less community resistance in low-income and communities of color, and therefore site their facilities there (Mohai and Saha, 2015). In essence, companies deliberately choose communities with little political clout and avoid thwarting efforts. So, it is theoretically possible that there are poor communities or communities with low education, but which still have political clout (e.g., money, influence). However, that explanation does not explicitly account for the historical processes which have deliberately decreased the political power of communities of color. The environmental racism hypothesis would posit that toxic facilities and other sources of pollution are disproportionately sited in communities of color as a direct result of government-endorsed racial discrimination (Mohai & Saha, 2015; Mohai & Saha, 2015). Clearly, further research is needed which incorporates and examines race as a predictor of hazard exposure in Sacramento County.

Limitations

Secondary data analyses are inherently limited in that the database is not created to address the specific research question (Cheng & Phillips, 2014). Accordingly, the variables might not precisely align with the researchers' variables of interest. In the present study, the dependent and independent variables are measured as percentile rank scores, rather than raw percentiles. A further limitation of secondary data analysis is that the researcher does not collect the data, and therefore does not know the methodological nuances (Cheng & Phillips, 2014). CalEPA does provide a detailed document regarding methodology, but it is nearly impossible for the researcher to know every detail and nuance of secondary data collection without being present (Cheng & Phillips, 2014).

There are also biases inherent to linear regression analyses. Multicollinearity, for example, refers to high correlations among independent variables; high degrees of multicollinearity will produce a large standard error of the regression coefficient (Allison, 1999). Consequently, it is more difficult to find statistically significant coefficients, and to distinguish between the individual effects of collinear independent variables (Allison, 1999). Furthermore, Pearson's correlation and multiple regression analyses are correlational research methods, meaning that they do not prove definitive causality. Although variables within a regression equation can be controlled for, extraneous and alternate variables cannot be controlled. In this study, the regression was split into four models due to multicollinearity bias; housing burden and unemployment were not included in the same model due to their collinearity.

This study is further limited because an indicator for race or ethnicity was not included. Research clearly established race as a significant predictor of pollution burden, and would be a valuable addition to the present analysis – and when informing environmental justice efforts more broadly (Mohai & Saha, 2015, Kemp, 2011). Race was not included due to a lack of data, and due to the researcher's interest in the varying predictive value of individual socioeconomic factors.

Limitations of CalEnviroScreen 3.0

Some researchers would hypothesize that the data collection methods used by CalEnviroScreen under - or inadequately - measure certain environmental hazards and demographic characteristics (Thompson, 2016; Greenfield, Rajan, & McKone, 2017; August, Faust, Cushing, Zeise, & Alexeeff, 2012). The creators of CalEnviroScreen themselves acknowledge and outline several limitations of their database and collection methods (Rodriguez & Zeise, 2017). The creators deliberately used solely publicly-available data on a small number of indicators to keep the process and model of pollution burden simple. Consequently, much of the demographic data was derived from the United States Census, and residential addresses used were limited to USPS zip codes. An example of this limitation lies in the measurement of drinking water quality, which may not be indicative of the "current state of water" within census tracts (Rodriguez & Zeise, 2017). Census tracts can encompass multiple public drinking water systems, so the measurement used to calculate the score of a given tract might not be indicative of what an individual within that tract is drinking (Rodriguez & Zeise, 2017). More locally-sourced data would be helpful in mitigating these inaccuracies/limitations, but it does not currently exist. Specific limitations of CalEnviroScreen or its method are discussed below.

Limitations of Indicators

For the groundwater threats indicator, CalEnviroScreen draws data solely from the State Water Resources Control Board's "GeoTracker" tool; however, this data source includes only point-source pollution of groundwater, and excludes non-point sources (Thompson, 2016). Non-point source pollution could include deteriorating septic systems or the application of toxic agricultural chemicals and pesticides (Thompson, 2016). Some research posits, however, that non-point source pollution poses a greater risk to human health than point-source pollution (Thompson, 2016). Furthermore, the GeoTracker tool does not include data on dairies or concentrated animal feeding operations (CAFOs), neglecting to measure communities' proximities to these sites (Thompson, 2016). Nonetheless, these sites significantly impact groundwater (Thompson, 2016). Finally, the GeoTracker tool fails to distinguish between communities that benefit from imported drinking water (i.e. Los Angeles County) and those dependent on groundwater (i.e. rural communities near Fresno) (Thompson, 2016). Due to these limitations, the groundwater threats indicator may underestimate or inaccurately identify the communities most affected by groundwater pollution.

Other indicators pose similar limitations, and underestimate vulnerable communities' pollution burden and exposures. For instance, the hazardous waste generators indicator includes data only from "large-generator" facilities; research indicates, however, that small generators release 97% of toxic pollutants in the county

(Thompson, 2016). Furthermore, the database does not take into consideration sites greater than 1000 meters away from census tracts; this is problematic because pollution from sites beyond 1000m can impact communities outside of that buffer (Thompson, 2016). Likewise, the cleanup sites indicator excludes sites greater than 1000m away from a given census tract; however, residents can experience increased stress due to the fear of contamination from sites more than 1000m away (Thompson, 2016). These methodological limitations underestimate vulnerabilities that rural communities face, therefore inhibiting disadvantaged communities from receiving grants or other funding to improve community conditions (Thompson, 2016).

Usage of Census-Derived Data

Exclusive usage of U.S. Census-derived data, including that from the American Community Survey, poses further limitations and has important implications. Data from the Census Bureau undercounts some of the most vulnerable communities and populations, including migrant and seasonal farmworkers, people of color (especially members of indigenous groups), economically disadvantaged people, linguistically isolated communities, and other marginalized populations within communities that often suffer from poverty, inadequate infrastructure, and insufficient resources which promote health and well-being (i.e. decent housing, public transportation, safe places to exercise, stores selling healthy foods, etc.) (Thompson, 2016).

Particularly in rural areas, large census tract sizes lead to skewed measures of poverty. Furthermore, census data on unemployment does not measure seasonal unemployment, which a significant portion of California's farmworkers experience

(Thompson, 2016). The overarching goal of CalEnviroScreen is "to assist California communities by directing state and potentially local government resources toward a common purpose: the revitalization of disadvantaged communities and the pursuit of environmental justice" (Rodriguez & Zeise, 2017). Accordingly, the database helps to determine which "disadvantaged communities" and "environmental justice communities" will receive state funding. However, its methodologies exclude some of California's most vulnerable communities from consideration for funding. Adoption and inclusion of more comprehensive data collection methods and risk assessment could help to fill in these data gaps.

Contribution to Environmental Justice

CalEnviroScreen contributes meaningfully to environmental justice, but it could improve by offering more comprehensive measures of pollution burden and vulnerabilities to the health impacts of hazard exposure. For instance, the tool could provide data on access to medical care and public transit options, two important determinants of access to resources which promote health and wellbeing (Thompson, 2016; Greenfield et al., 2017). Additionally, it could incorporate more localized data sources, which measure more accurately the composition of communities - and the resources or risks therein (Thompson, 2016; Greenfield et al., 2017).

The limitations of the present study inevitably mirror those of the CalEnviroScreen database. It is important to take the methodological limitations into consideration when interpreting the results within Sacramento County. Despite these limitations, socioeconomic disadvantages were significantly correlated with pollution burden, and poverty was a significant predictor of pollution burden in Sacramento County. Presumably, improvements to the CalEnviroScreen method would only increase predictions of pollution burden by socioeconomic disadvantages. Accordingly, action must be taken to promote environmental justice and decrease health disparities due to man-made environmental health hazards.

Implications for Social Work Practice

An enduring challenge in the environmental justice movement is the accurate quantification of health risks resulting from exposure to toxic environmental pollutants (Mah, 2016). The cultural and scientific movement towards "big data" is a phenomenon that emphasizes the need for large-scale, large quantity data to increase problem-solving efficiency and advance social, environmental, or other causes (Mah, 2016). However, big data in environmental justice is often collected by large-institutions, such as the U.S. Census Bureau or CalEPA (Mah, 2016). As outlined above, the large institutions which collect data are often implicated in the root causes of environmental issues (i.e. degradation, inequality) (Mah, 2016). Consequently, databases are increasingly far-reaching but lack the comprehensiveness and utility produced by "citizen-expert alliances" – methods upon which environmental justice movements have historically relied (Mah, 2016). Social workers have an ethical commitment to advance social justice, and therefore to advance environmental justice. Social workers are well equipped to engage in advocacy and alliance-building efforts that improve the quality of environmental risk assessments, and therefore decrease socioeconomic disparities in pollution exposure.

Accurate risk assessment procedures before siting could deter the placement of hazardous facilities or sites in low-income and communities of color (Mohai & Saha 2015, Mohai & Saha 2015, & Mohai & Saha, 2007). Big data focuses on immediate solutions to acute environmental issues; however, environmental hazard exposure tends to manifest in chronic, non-acute health effects (Mah, 2016). With a lack of longitudinal, scientific data regarding health issues, corporations can ignore the health implications of their practices (Mah, 2016). Citizen-expert alliances have exposed corporations' wrong doing, but only in the worst cases of environmental injustice; the lack of longitudinal scientific evidence of negative health outcomes is a significant barrier to environmental justice advocacy (Mah, 2016; Philip & Reisch, 2015). Social workers could foster interdisciplinary collaboration between communities, human rights advocates, environmental researchers, and politicians, advancing environmental justice via comprehensive and culturally-responsive risk assessments (Philip & Reisch, 2015).

Although social workers aim to advance racial and economic justice, they do not traditionally receive education in environmental issues (Philip & Reisch, 2015). Future research should identify ways in which environmental advocacy can be integrated into social work education such that the field prepares environmental justice advocates and professionals (Philip & Reisch, 2015; Kemp, 2011). Environmental justice is social justice, and social workers are ethically mandated to promote the physical and mental health equity of marginalized populations (Kemp, 2011).

Conclusion

In a secondary analysis of the CalEnviroScreen database, socioeconomic factors were significantly correlated with pollution burden, and poverty was revealed to be the most significant predictor of pollution burden. Despite the limitations of CalEnviroScreen and multiple regression analysis, pollution burden is significantly predicted by poverty, and it is therefore necessary to promote and improve the well-being of communities with high levels of poverty. Further research considering racial and ethnic demographics would help in the formulation of culturally-responsive interventions to reduce pollution burden in low-income communities. Social work values align with environmental justice efforts; education and training should incorporate environmental issues.

Appendix A

Description of CalEnviroScreen Indicators

Indicator (Abbreviation)	Calculation	Data Source
Pollution Burden (Exposures Component)		
Ozone Concentrations in Air (Ozone)	Mean of summer months (May - October) of daily maximum 8-hour ozone concentration (ppm), averaged over three years (2012-2014)	Air Monitoring Network, California Air Resources Board (CARB)
PM 2.5 Concentrations in Air (PM 2.5)	Annual mean concentration of PM2.5 (avg of quarterly means, microgram per cubic meter) over three years (2012-2014)	Air Monitoring Network, CARB
Diesel Particulate Matter Emissions (Diesel PM)	Spatial distribution of gridded diesel emissions from on-road and non-road sources for a 2012 July summer day (kg/day)	CARB, San Diego Association of Governments (SANDAG)
Drinking water contaminants (Drinking Water)	index of average contaminant concentrations over one compliance cycle (2005-2013)	California Department of Public Health (CDPH): Drinking Water Systems Georgraphic Reporting Tool, California Environmental Health Tracking Program; Public Water System Location Data Permitting/Inspections/Compliance/Monitoring /Enforcement (PICME) database; Water Quality Monitoring Database. United States Environmental Protection Agency (US EPA): Safe Drinking Water Information System. State Water Resources Control Board: Domestic Well Project, Groundwater Ambient Monitoring and Assessment (GAMA) Program. State Water Resources Control Board and US Geological Survey: Priority Basin Project, GAMA Program
Use of certain high hazard, high volatility pesticides (Pesticides)	Total pounds of active pesticide ingredients (selected for hazard and volatility) used in agriculture per square mile, averaged over 3 years	California Department of Pesticide Regulation (DPR), Pesticide Use Reporting
Toxic releases from facilities (Tox. Release)	Toxicity-weighted concentrations of modeled chemical releases to air from facility emissions and off-site incineration (averaged over 2011 - 2013)	Risk Screening Environmental Indicators (RSEI); US EPA; Toxic Release Inventory (TRI); Mexico Registry of Emissions and Pollutant Transfer (RETC)

Traffic density (Traffic)	Traffic density - sum of traffic volumes adjusted by road segment length (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of census tract boundary (2013)	California Environmental Health Tracking Program (CEHTP); CDPH; US Department of Transportation and US Customs Border Protection; SANDAG
Pollution Burden (Environmental Effects Component)		
Toxic cleanup sites (Cleanup Sites)	Sum of weighted sites within each census tract	EnviroStor Cleanup Sites Database, Department of Toxic Substance Control (DTSC); US EPA, Region 9 NPL Sites Polygons
Groundwater threats from leaking underground storage sites and cleanups (Groundwater Threats)	Sum of wiehgted scores for sites within each census tract	GeoTracker Database, State Water Resources Control Board (SWRCB)
Hazardous waste facilities and generators (Haz. Waste)	Sum of weighted permitted hazardous waste facilities and hazardous waste generators within each census tract	EnviroStor Cleanup Sites Database, Department of Toxic Substance Control (DTSC); US EPA, Region 9 NPL Sites Polygons
Impaired water bodies (Imp. Water Bodies)	Summed number of pollutants across all water bodies designated as impaired within the area in 2012	303(d) mList of Impaired Water Bodies, SWRCB
Solid waste sites and facilities (Solid Waste)	Sum of weighted solid waste sites and facilities (as of December 2016)	Solid Waste Information System (SWIS), Closed, Illegal, and Abandoned (CIA) Disposal Sites Program, California Department of Resources Recycling and Recovery, CalRecycle, Hazardous Waster Tracking System - Department of Toxic Substances Control (DTSC)
Population Characteristics (Sensitive Populations Component)		
Asthma emergency department visits (Asthma)	Spatially-modeled, age-adjusted rate of emergency department visits for asthma per 10,000 (averaged over 2011-2013)	California Office of Statewide Health Planning and Development (OSHPD), California Environmental Health Tracking Program (CEHTP), California Department of Public Health
Cardiovascular disease (Cardiovascular Disease)	Spatially-modeled, age-adjusted rate of emergency department visits for acute myocardial infarction (AMI) per 10,000 (averaged over 2011-2013)	California Office of Statewide Health Planning and Development (OSHPD), California Environmental Health Tracking Program (CEHTP), Environmental Health Investigations Branch, California Department of Public Health

Low birth-weight infants (Low Bierth Weight)	Percent of low birth weight, averaged over 2006-2012	California Department of Public Health (CDPH)
	Population Characteristics (Socioeconomic Factors Component)	
Educational Attainment (Education)	Percent of the population over age 25 with less than a high school education (5-year estimate, 2011-2015)	American Community Survey, US Census Bureau
Housing burdened low income households (Housing Burden)	Percent of households in a census tract that are both low income (making less than 80% of the HUD Area Median Family Income) and severely burdened by housing costs (paying greater than 50% of their income to housing costs). (5-year estimates, 2009-2013).	Housing and Urban Development Comprehensive Housing Affordability Strategy, American Community Survey, US Census Bureau
Linguistic isolation (Linguistic Isolation)	Percent limited English-speaking households, (2011-2015).	American Community Survey, US Census Bureau
Poverty (Poverty)	Percent of the population living below two times the federal poverty level (5-year estimate, 2011-2015).	American Community Survey, US Census Bureau
Unemployment (Unemployment)	Percent of the population over the age of 16 that is unemployed and eligible for the labor force. Excludes retirees, students, homemakers, institutionalized persons except prisoners, those not looking for work, and military personnel on active duty (5-year estimate, 2011-2015).	American Community Survey, US Census Bureau

Adapted from Rodriguez & Zeise (2017)

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