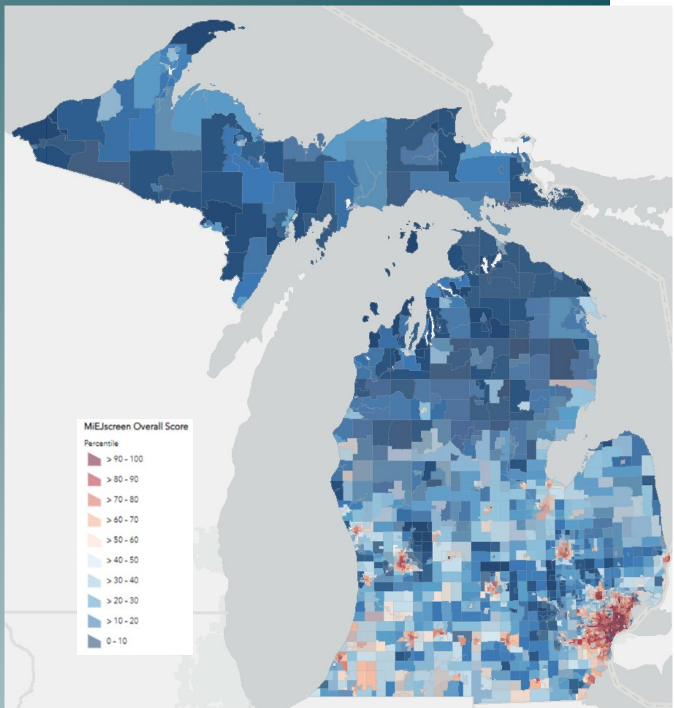

MiEJScreen

Michigan **E**nvironmental **J**ustice Mapping and **S**creening Tool

DRAFT TECHNICAL REPORT

March 2022

EGLE | MICHIGAN DEPARTMENT OF ENVIRONMENT, GREAT LAKES, AND ENERGY

Office of the Environmental Justice Public Advocate

800-662-9278 | Michigan.gov/EGLE

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Integrating equity and environmental justice into state government is vital for the state of Michigan. Governor Whitmer's Executive Order 2019-06 created the Office of the Environmental Justice Public Advocate (OEJPA) and the Interagency Environmental Justice Response Team (IEJRT) within EGLE with the goal of assuring all Michigan residents benefit from the same protections from environmental hazards and to work to achieve Michigan's goal of becoming a national leader in achieving environmental justice. The executive order named the Department of Agriculture and Rural Development, Civil Rights, Health and Human Services, Natural Resources, Transportation, the Michigan Strategic Fund, and the Public Service Commission to the IEJRT. Since its inception, several other state agencies were invited to provide a comprehensive picture of programs and policies affecting environmental justice communities.

With these goals in mind, and to achieve the priorities of the OEJPA and IEJRT, four workgroups were formed with representation from departments on the IEJRT. The four workgroups include: Communications and Outreach, Research and Data, Planning and Policy, and Training. The primary objective of the Research and Data Workgroup since it began meeting in December 2019 has been the development of the Michigan Environmental Justice Mapping and Screening Tool or MiEJScreen.

This report details the development of a Michigan specific tool to identify communities most affected by cumulative environmental health impacts. MiEJScreen is modeled after California's CalEnviroScreen. The tool uses a science-based method to evaluate multiple pollution sources in a community, while also accounting for community vulnerabilities to pollution's adverse effects and considering the socioeconomic and health status of people living in the community.

Environmental Justice in Michigan

Michigan defines environmental justice as the equitable treatment and meaningful involvement of all people, regardless of race, color, national origin, ability, or income and is critical to the development and application of laws, regulation, and policies that affect the environment, as well as the places people live, work, play, worship, and learn.

The quest for environmental justice has a long history in Michigan. Community advocates have called on the state to address injustices facing their communities for decades. In response, the state engaged with multiple stakeholders to discuss, research, and develop recommendations to address environmental justice issues. The first such effort was undertaken in 1988 by what was then the Michigan Department of Environmental Quality (DEQ) with the development of an Environmental Justice Workgroup, which produced several recommendations. In 2005, the DEQ's Environmental Advisory Council was tasked with assessing the condition of environmental justice in Michigan and considering opportunities for state policy on environmental justice. Their efforts culminated in the 2006 Recommendations for an Environmental Justice Policy. These recommendations led to former Governor Granholm's Executive Directive 2007-23 that charged the DEQ with developing and implementing a state environmental justice plan to promote environmental justice in Michigan.

In 2017, former Governor Snyder created the Environmental Justice Work Group (EJWG) following direct recommendations from the Flint Water Advisory Task Force and the Flint Water Interagency Coordinating Committee's Policy Subcommittee. The EJWG was charged with developing recommendations to improve environmental justice awareness and engagement. The EJWG was composed of 23 members, representing environmental justice communities across the state, environmental organizations, businesses, state and local government bodies, academia, and federally recognized tribes. The 33 recommendations, compiled in the Environmental Justice Work Group Report (Environmental Justice Work Group, 2018), include environmental justice guidance, training, curriculum, and policies which further increase quality of life for all Michiganders. Recommendations from the report formed the basis for the creation of the OEJPA and the IEJRT. The report's priorities including a recommendation to develop an environmental justice screening tool in Michigan and include cumulative impacts in the decision-making processes.

One of the purposes of developing the MiEJScreen is to provide decision-makers and advocates with current, easy-to-understand data on environmental conditions and vulnerable populations. The data can then be used to inform policy and resource allocation decisions to address environmental justice issues.

Development of MiEJScreen

MiEJScreen was developed through collaboration with several state departments and evaluation of environmental justice mapping tools, including California's CalEnviroScreen and the U.S. Environmental Protection Agency's (EPA's) EJSCREEN, and similar tools from other states and municipalities. Research conducted by graduate students from the University of Michigan also contributed to the tools development by examining the feasibility of creating a Michigan-specific screening tool relevant to environmental justice (Grier et al., 2019) and provided recommendations on the development of a screening tool in Michigan (Blondell et al., 2020).

Community voices also contributed to development of MiEJScreen. The OEJPA sought input from various stakeholders, including the Michigan Advisory Council on Environmental Justice and the 102 participants in eight Regional Roundtables held across the state. The draft tool is also being released for public review and comment. Comments and feedback on MiEJScreen can be submitted to EGLE-EnvironmentalJustice@michigan.gov or via U.S. mail to the address below:

Office of Environmental Justice Public Advocate
Constitution Hall
P.O. Box 30473
Lansing, MI 48909-7973

The tool will be updated every three to four years as new data become available and to provide the most current data. In addition, we continue to explore additional indicators and seek input from stakeholders. We welcome opportunities to partner with others in continuing this work. Please contact us at EGLE-EnvironmentalJustice@michigan.gov.

Purposes and Intended Uses of MiEJScreen

The primary purpose of MiEJScreen is to examine and map environmental, health, and socioeconomic indicators to identify communities in Michigan that may be disproportionately impacted by environmental hazards. While the full uses and purposes of the tool will develop over time, other environmental justice mapping and screening tools have been used to prioritize resource allocation, identify areas for additional outreach, guide policy decisions, and prioritize programs such as redevelopment or enforcement. MiEJScreen is designed to be used by multiple stakeholders.

The tool allows users to explore locations at a detailed geographic level, regionally, or across the entire state. Environmental indicators typically are direct or proxy estimates of risk, pollution levels, or potential exposure (e.g., due to nearby facilities). Health and socioeconomic indicators are often used as proxies for a population's vulnerability or susceptibility to pollution. The tool is designed to provide an overall cumulative score but also to be able to view indicators separately or in combination.

The screening tool is a useful first step in understanding or highlighting locations that require further review. It is important to understand that screening tools do not provide a complete assessment of risk and have significant limitations.

Caveats and Limitations of MiEJScreen

MiEJScreen is a screening tool to help identify potential areas of environmental justice concern. The tool does not provide data on every environmental impact, health impact, or demographic factor. To fully assess community needs and adequately address environmental justice concerns, supplemental information and local knowledge should be considered.

Datasets selected for inclusion in the tool represent the most recent data that were available at the time of each indicator's development. It is important to note that the inclusion of a dataset does not imply it is the newest, best, or primary estimate of actual conditions or risks. Future updates of the tool will use the most recent and relevant data available.

Many environmental concerns are not yet included in comprehensive, nationwide, or statewide databases and therefore are not reflected in this tool. For example, data on environmental indicators such as sulfur dioxide and indoor air quality were not available with adequate quality, coverage and/or resolution to be included in this tool.

Another important limitation is that the tool relies on demographic and environmental estimates that involve substantial uncertainty, especially when looking at a small geographic area, such as a single Census tract. Another uncertainty is the fact that the environmental indicators are only screening-level proxies for actual exposure or risk. This is the case for the proximity indicators. However, the model and methodology used is considered useful in identifying communities burdened by multiple sources of pollution with populations that may be especially vulnerable.

While environmental conditions can influence public health, so can many other factors, including socioeconomic indicators, behavioral and genetic risk factors, level of preventive care, and quality of and access to health care. Therefore, the health indicators presented here are broad, are not intended to represent specific diseases or conditions related to the environment, and cannot alone be used to draw conclusions about how exposure to environmental contaminants influences public health. They do, however, provide important context for indicators for environmental contaminants that may be a risk factor.

Locations with high scores for many of the indicators are most likely to be identified as impacted. Since there are tradeoffs in combining different sources of information, the results are considered most useful for identifying communities that score highly using the model. An analysis of the sensitivity of the CalEnviroScreen model (Faust et al., 2017), using a limited data set, to changes in weighting showed it is relatively robust in identifying more impacted areas (Meehan August et al., 2012). Therefore, use of broad groups of areas, such as those scoring in the highest 15 and 20 percent, is expected to be the most suitable application of the MiEJScreen results.

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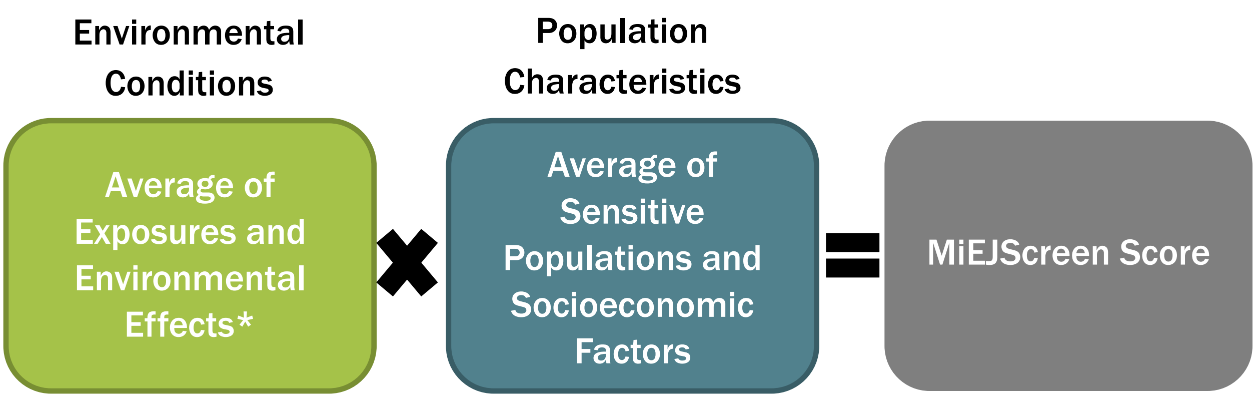
OVERVIEW OF DATA AND METHODS

The Model

The model to develop Michigan's environmental justice screening tool is based on California's CalEnviroScreen. CalEnviroScreen is a place-based model that provides information for the entire state on a geographic basis (census tract level). It includes multiple indicators as contributors to cumulative impacts representing environmental conditions and factors that affect people's vulnerability to environmental pollution.

The MIEJScreen overall score is made up of two sub scores (Environmental Conditions and Population Characteristics) which are further divided into four categories. There are two categories representing Environmental Conditions: Exposures and Environmental Effects, and two categories representing Population Characteristics: Sensitive Populations and Socioeconomic Factors. Each of the categories has a set of indicators that are scored for each census tract by its raw value, then assigned percentiles based on rank-order. Those percentile scores are averaged for each of the four categories (Exposures, Environmental Effects, Sensitive Populations, and Socioeconomic Factors). The formula below is used to combine the scores for each category to calculate the overall MiEJScreen Score:



*The Environmental Effects category is weighted one-half when combined with the Exposures category.

Environmental Conditions

The environmental effects and exposure indicators included in this sub score represent the environmental conditions and potential environmental risk factors present in Michigan's communities.

Environmental Exposure

Indicators within the environmental exposure category provide data on the sources, concentrations, and releases of pollutants as a measure of potential pollution exposure. Most of these Environmental Exposure indicators are air quality related issues.

Exposure can be thought of as the interaction of individuals or populations with a substance due to its presence in or movement through the environment (air, water, food, soil). Ingesting, inhaling, or otherwise interacting with the substances generated or described by some of the indicators in this category have been associated with poor health outcomes. For example, exposure to high levels of ambient ozone has been associated with reductions in lung functioning (U.S. EPA, 2006b).

All indicators within this category are weighted and contribute equally to the environmental conditions sub score.

Environmental Effects

Environmental effects indicators account for adverse environmental factors that may contribute to poor environmental quality, even when population exposure with the environmental hazard is unknown or uncertain. These Environmental Effects indicators generally show proximity to known or potential contamination sites.

Living in proximity to environmental degradation such as impaired water bodies or cleanup sites, as this category represents, can affect the health of communities in several ways. Several of the indicators included in this category have been associated with the prevalence of diseases ranging from cardiovascular to reproductive. Additionally, living in environmentally degraded communities can cause members to feel stressed and unsafe, both of which are risks to human health. Poor environmental quality may also prevent community members from enjoying or utilizing the many services ecosystems provide, including those that are associated with health benefits such as outdoor recreation.

Importantly, as the environmental effects indicators represent only proximity to potential exposure rather than true exposure, this category is weighted by half its total when factored into the MiEJScreen score to better reflect the risk to nearby populations. All indicators within this theme are weighted and contribute equally to the environmental conditions sub score.

Population Characteristics

The sensitive populations and socioeconomic factors in this sub score reflect both biological and societal vulnerabilities found in communities that can increase their susceptibility to environmental conditions.

Sensitive Populations

Sensitive population indicators refer to human populations that experience increased susceptibility to environmental health risk factors such as pollution. Such populations include individuals with impaired health conditions due to disease and genetic factors.

Pollution is not only a likely contributor to the generation of such conditions but has also been found to worsen them. For example, exposure to environmental pollutants is both a known risk factor for developing asthma, an indicator within this category, and a known trigger for asthma attacks.

All indicators within this category are weighted and contribute equally to the population characteristics sub score.

SOCIOECONOMIC FACTORS

Socioeconomic factors cover indicators related to environmental justice conditions that alter the effects of environmental conditions on community health.

The susceptibility of communities of color and low-income populations to various environmental conditions has been reaffirmed many times through research. Studies have found non-White populations to be more likely to live in proximity to air pollution and to experience negative health outcomes associated with exposure such as cardiovascular disease, miscarriages, and even death. Other socioeconomic factors that represent increased vulnerability have also been included.

All indicators within this category are weighted and contribute equally to the population characteristics sub score.

The selection of specific indicators requires consideration of both the type of information that will best represent statewide environmental conditions and population characteristics, and the availability and quality of such information at the necessary geographic scale statewide.

Indicator and Category Scoring

For each indicator raw values or percentages for each census tract were ranked from highest to lowest. Each census tract was then assigned a percentile score based on its rank among the other tracts' indicator values. Then, for each tract the percentile scores of all indicators within a particular category were averaged. These averaged cores were then ranked and a percentile assigned.

For example, in a given census tract the sensitive population indicators would be assigned a percentile score based on the data value that geographical location has compared to all other census tracts in the state. These indicator percentile scores, which would include asthma, cardiovascular disease, low birth weight, life expectancy, and blood lead level, would be added together and divided by the number of indicators or in this case, five. This gives the average percentile score for all sensitive population indicators compared to those in other Michigan census tracts. The same procedure is done for each category: environmental effects, environmental exposure, and socioeconomic factors.

Categories were then grouped under their respective sub score; environmental effects and environmental exposures fall under environmental conditions and population characteristics includes both sensitive populations and socioeconomic factors. Sub scores were then determined for each census tract by the following procedure:

- Environmental Conditions: As mentioned above, the percentiles for indicators within each category were averaged. To generate a total environmental conditions score, the environmental effects indicators average percentile score was weighted at one half of its original value then averaged with the environmental exposure indicators average score. This is done to reflect the actual risk to human health associated with environmental effect indicators as they only represent proximity to potential exposure.

- Population Characteristics: The averaged percentile scores for indicators in the sensitive populations and socioeconomic factor categories were added together and averaged to get a total population characteristics score for each census tract.

The Environmental Conditions and Population Characteristics scores were then scaled and assigned a value between 0 and 10. The scaling ensures that the environmental conditions and population characteristics sub scores contribute equally to the overall MiEJScreen score.

The overall MiEJScreen score is calculated by multiplying the Pollution Burden and Population Characteristics scores. Since each group has a maximum score of 10, the maximum MiEJScreen Score is 100.

Census tracts are then ordered from highest to lowest, based on their overall score. A percentile for the overall score is then calculated from the ordered values.

Maps are developed showing the percentiles for all the census tracts of the state. Maps are also developed highlighting the census tracts scoring the highest.

Categories	**Environmental Exposure**	**Environmental Effects**	**Sensitive Populations**	**Socioeconomic Factors**
Indicators	NATA Air Toxics Cancer Risk NATA Respiratory Hazard Index NATA Diesel Particulate Matter Particulate Matter ($PM_{2.5}$) Ozone Traffic Density	Proximity to Cleanup Sites Proximity to Hazardous Waste Facilities Impaired Water Bodies Proximity to Solid waste Sites and Facilities Lead Paint Indicator Proximity to RMP Sites Wastewater Discharge Indicator	Asthma Cardiovascular Disease Low Birth Weight Infants Blood Lead Level Life Expectancy	Low Income Population Black, Indigenous, People of Color Population Educational Attainment Linguistic Isolation Population Under Age 5 Population Over Age 64 Unemployment Housing Burden
Sub Scores	**Environmental Conditions** (Average percentile of Environmental Exposure indicators + 0.5 x average percentile of Environmental Effects indicators) 1.5		**Population Characteristics** (Average percentile of Sensitive Population indicators + average percentile of Socioeconomic Factor indicators) 2	
Score	**Final Composite Score = Environmental Conditions score x Population Characteristics score** **MiEJScreen Score**			

How to Interpret the Map

Percentile scoring for this map can be interpreted to measure relative environmental risk factors in communities. The percentiles help compare various factors that may contribute to disparities within a community or between communities and should not be taken to be an absolute value.

This map also does not model the overall burden on communities, nor does it reflect the actual number of individuals affected by environmental risk factors. This map also does not model the positive or negative likelihood of an individual health outcome.

Therefore, it should not be used to diagnose a community health issue, to label a community or to attribute risk factors and exposures for specific individuals. Additional analysis is needed to make decisions on health outcomes that may be associated with the environmental risk factors. This map is intended to be a dynamic, informative tool. Decisions on the cumulative impact of environmental risk should not solely be based on this map.

Individual Indicators: Description and Methods

Environmental Conditions: Environmental Exposure

Environmental Conditions: Environmental Exposure Indicators

Indicator	Details	Source	Data Year
NATA Air Toxics Cancer Risk	Lifetime cancer risk from inhalation of air toxics	EPA EJSCREEN, retrieved 2020	2014
NATA Respiratory Hazard Index	Air toxics respiratory hazard index (ratio of exposure concentration to health-based reference concentration)	EPA EJSCREEN, retrieved 2020	2014
NATA Diesel Particulate Matter	Diesel particulate matter level in air, µg/m3	EPA EJSCREEN, retrieved 2020	2014
Particulate Matter ($PM_{2.5}$)	$PM_{2.5}$ levels in air, µg/m3 annual average	EPA EJSCREEN, retrieved 2020	2016
Ozone	Ozone summer seasonal average of daily maximum 8-hour concentration in air in parts per billion	EPA EJSCREEN, retrieved 2020	2016
Traffic Density	Traffic density within a buffered (150 meters) census tract, normalized vehicles per day/adjusted length-based road (miles)	Michigan Department of Transportation, Annual average daily traffic (AADT) volumes and National functional classification (NFC) data files	2019

NATA Air Toxics Cancer Risk, NATA Respiratory Hazard Index and NATA Diesel Particulate Matter

Air toxics, often referred to as hazardous air pollutants (HAPs), are pollutants that are known or suspected to cause cancer or other serious health effects, such as reproductive effects or birth defects, or adverse environmental effects. HAPs are emitted from a wide variety of sources including motor vehicles, industrial facilities, and power plants. In some cases, these substances react with other constituents in the atmosphere or break down into other chemicals.

A comprehensive list of EJ studies using the NATA database can be found in Chakraborty et al., (2011). Some example studies of chemicals listed as HAPs include Morello-Frosch & Jesdale (2006), and other studies reviewed by Liu (2001) and Brender et al., (2011). Diesel particulate matter has also been the subject of EJ analysis (Rosenbaum, Hartley, & Holder, 2011).

Indicator

The following indicators are used from the EPA's EJSCREEN:

- NATA Air Toxics Cancer Risk: Lifetime cancer risk from inhalation of air toxics (2014).
- NATA Respiratory Hazard Index: Air toxics respiratory hazard index (ratio of exposure concentration to health-based reference concentration) (2014).
- NATA Diesel Particulate Matter: Diesel particulate matter level in air, µg/m3.

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2020.

Method

EJSCREEN uses the most recent data from EPA's National-Scale Air Toxics Assessment (NATA). NATA estimates cancer risk and noncancer implications of many of the 187 air pollutants classified as HAPs. For more information, refer to EJSCREEN Technical Documentation: www.epa.gov/ejscreen/technical-documentation-ejscreen.

The EPA's National Air Toxics Assessment (NATA) website has extensive documentation of all of the data and methods used in developing the NATA indicators, as well as discussions of uncertainty, caveats, and limitations in the NATA estimates. NATA documentation and a discussion of these issues can be found here www.epa.gov/national-air-toxics-assessment.

Particulate Matter ($PM_{2.5}$)

PM2.5 is particulate matter that is 2.5 microns or less in diameter. Common sources of PM2.5 emissions include power plants and industrial facilities. Secondary PM2.5 can form from gases, such as oxides of nitrogen (NOx) or sulfur dioxide (SO2), reacting in the atmosphere.

The EPA's work associated with the PM NAAQS has documented the health effects associated with exposure to PM2.5, including elevated risk of premature mortality from cardiovascular diseases or lung cancer, and increased health problems such as asthma attacks (U.S. EPA, 2009b).

Indicator

Particulate Matter (PM2.5) levels in air, µg/m3 annual avg. (2016)

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2020.

Method

EJSCREEN's particulate matter data are estimated by EPA from a combination of monitoring data and air quality modeling. For more information, refer to EJSCREEN Technical Documentation: www.epa.gov/ejscreen/technical-documentation-ejscreen

Ozone

Ozone is one of six criteria air pollutants identified by USEPA's National Ambient Air Quality Standards (NAAQS). In the upper atmosphere ozone provides protection against the sun's ultraviolet rays. Ozone at ground level is the primary component of smog. Ozone (O3) is not usually emitted directly into the air but is created at ground level by a chemical reaction between oxides of nitrogen (NOx) and volatile organic compounds (VOCs) in the presence of sunlight. These ozone precursors are emitted by motor vehicles, industrial facilities, and power plants as well as natural sources.

Toxicological and epidemiological studies have established an association between exposure to ambient ozone and a variety of health outcomes, including reduction in lung function, increased inflammation and increased hospital admissions and mortality (U.S. EPA, 2006b).

Individuals most susceptible to the effects of O3 exposure include those with a pre-existing or chronic respiratory disease, children who are active outdoors and adults who actively exercise or work outdoors.

Indicator

Ozone summer seasonal average of daily maximum 8-hour concentration in air in parts per billion. (2016)

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2020.

Method

EJSCREEN's ozone data are estimated by the EPA from a combination of monitoring data and air quality modeling. For more information, refer to EJSCREEN Technical Documentation: www.epa.gov/ejscreen/technical-documentation-ejscreen

TRAFFIC DENSITY

Living close to high traffic densities have been known to lead to increased exposure to noise, vibration, and local land use changes, in addition to traffic-related air pollution (Boehmer et al., 2013). The increased exposure to noise from living near higher traffic densities can often lead to sleep disturbances leading to a poorer quality of life (Eze et al., 2017).

Adverse health effects such as cardiovascular disease mortality, respiratory health and an increased risk of low birth weight are all associated with exposure to traffic-related air pollution (Berglind et al., 2009; Ghosh et al., 2012; Habermann & Gouveia, 2012; Kan et al., 2007; von Klot et al., 2009). An increased risk of cardiovascular disease is also related to long-term exposure to traffic-related air pollution (Kaufman et al., 2016).

Exposure to traffic-related air pollution may also predispose children to negative respiratory health outcomes (Gauderman et al., 2007; Gunier et al., 2003; Shultz et al., 2012).

Indicator

Traffic density within a buffered (150 meters) of a census tract, normalized vehicles per day/adjusted length-based road (miles)

Data Source

Calculated 2019 Annual average daily traffic (AADT) volumes and National functional classification (NFC) data files from Michigan Department of Transportation.

Method

The method used for calculating is based on CalEnviroScreen and includes:

- A geographic information system (GIS) process, an overlay, was performed on specific GIS data files that included:
    - 2019 AADT volumes
    - National Functional Classification (NFC)

The overlay is used in identifying the Federal-aid network based off NFC values by road

- A query was applied to the export of the overlay to produce only the Federal-aid road segments and their corresponding AADTs.
- A 150 meter or approximately 500 feet buffer was placed around each 2010 census tract in Michigan. This buffer distance was determined to be a threshold where most particulate air pollution from traffic drops off (CARB, 2005).
- The buffered census tracts were intersected using the queried traffic volumes and roads. For each road within the buffer, a length-adjusted volume was calculated and summed for all roads in the buffer.
- Traffic density was calculated by dividing the sum of all the length-based traffic volumes within the buffered census tracts by the sum of the length of all roads within the buffered census tract.

For more information, refer to CalEnviroScreen 3.0 Report https://oehha.ca.gov/media/downloads/calenviroscreen/report/ces3report.pdf.

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Environmental Conditions: Environmental Effects Indicators

Indicator	Details	Source	Data Year
Proximity to Cleanup Sites	Proximity to Part 201 cleanup sites, Part 213 leaking underground storage tank sites, and Superfund sites (EPA NPL).	EGLE, Remediation and Redevelopment Division and EPA Superfund-NPL Sites (retrieved 2020)	2020
Proximity to Hazardous Waste Facilities	Proximity to hazardous waste facilities (TSDFs and LQGs).	EPA EJSCREEN (retrieved 2020) and EGLE, Material Management Division	2020
Impaired Water Bodies	Summed number of pollutants across all water bodies designated as impaired within the area.	EGLE, Water Resources Division 303(d) List of Impaired Water Bodies	2020
Proximity to Solid Waste Sites and Facilities	Proximity to Part 115 licensed landfills, old dumpsites, and scrap tire sites	EGLE, Material Management Division	2020
Lead Paint Indicator	Percent of housing built before 1960	EPA EJSCREEN (retrieved 2021)	2014-2018
Proximity to RMP Sites	Proximity to facilities with Risk Management Plans	EPA EJSCREEN (retrieved 2021)	2020
Wastewater Discharge Indicator	Toxicity-weighted concentrations in stream segments within an area	EPA EJSCREEN (retrieved 2021)	2020

Proximity to Cleanup Sites

Land that has suffered environmental degradation due to contamination by hazardous substances must undergo clean up efforts to be safe and usable. EGLE staff and property owners follow a process of investigating, remedial action, and monitoring to restore such sites. EGLE's remediation team maintain information about the state's cleanup efforts that can be found on their webpage. It can take years to investigate and fully remediate a site and during this time there are real concerns about the impact these sites have of human and environmental health. Additionally, contaminated sites can create a number of health risks as hazardous substances can move beyond the site through volatilization, groundwater plume migration, or windblown dust. Studies have shown that levels of contaminates organochlorine pesticides and toxic metals in the blood and house dust respectively correlated positively with residents' proximity to clean up sites (Gaffney *et al.* 2005; Zota *et al.* 2011).

Superfund-NPL sites are also captured in this indicator and refer to some of the nation's most contaminated land including manufacturing facilities, processing plants, landfills, and mining sites. The 1980 Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) established a federal "Superfund" for enforcement authorities to clean up major sites where hazardous waste has been improperly managed and now poses a significant public and environmental health risk. EGLE administers this program in Michigan and maintains data on the various sites across the state.

There are several studies that have assessed the health risks for people living near superfund sites. Such research has linked low birthweight, increased prevalence of liver disease and adult cancers with living in proximity to a Superfund-NPL site (Ala et al. 2006; Amin et. al, 2018; Baibergenova et al. 2003). Counties in the US which house Superfund sites are also more likely to have higher rates of ethnic and racial minorities living in them (Amin et. al, 2018).

Indicator

Proximity to Part 201 cleanup sites, Part 213 leaking underground storage tank sites, and Superfund sites (EPA NPL).

Data Source

Michigan EGLE Enviromapper: Sites of Environmental Contamination (Part 201) Leaking Underground Storage Tanks (Part 213) and USEPA EJSCREEN Superfund Sites (EPA NPL).

Method

The method used for calculating tract scores was the CalEnviroScreen: Site Weight-Multi-Ringed Buffer Proximity Method (Faust *et al.* 2017; Walker Weiland personal communication, 2020) See Appendix A for more details.

PROXIMITY TO HAZARDOUS WASTE FACILITIES

Waste products are considered hazardous if it has or may have harmful effects on human health or the environment. Hazardous waste products may be liquids, solids, or contained gases. Many discarded materials and by-products from industrial, mining, and agricultural operations or community activities are considered hazardous. The EPA and EGLE have requirements and maintain data regarding the generation, treatment, storage and disposal of such waste. Regulation and licensing programs also manage the transportation of hazardous wastes and inform citizens of proper handling of household hazardous waste. Most hazardous waste products must be transported in accordance with regulations from the location it was generated to a permitted Treatment, Storage, and Disposal Facility (TSDF) or recycling facilities. Due to the hazardous nature of these materials, there is widespread concern for the health of the people and environment surrounding such sites. Even though these are designed to prevent hazardous waste contamination, negative perceptions of hazardous waste facilities (HWF) can have significant impacts on the economic, social, and health outcomes of the surrounding areas.

The potential health effects that come from living near hazardous waste disposal sites have been examined in several studies (Vrijheid, 2000). Although there is generally limited data on the exposure of nearby populations, studies have found health effects such as diabetes and cardiovascular disease are significantly linked with living in proximity to HWF (Kouznetsova et al., 2007; Sergeev and Carpenter, 2005).

Protests against the disproportionate distribution of HWFs in communities of color originally brought environmental justice into the public consciousness. The 1982 non-violent sit-in protesting a hazardous chemical landfill in the majority-Black community of Warren County, NC failed to prevent the facility's siting, but paved a pathway for government action on environmental justice (Konisky, 2009). Research has since validated community concerns; Mohai and Saha (2007) found that despite only making up 25% of the population in 1990, people of color made up 40% of the population living with a mile of hazardous waste TSDFs.

Indicator

Proximity to hazardous waste facilities (TSDFs and LQGs).

Data Source

Michigan Part 111 Treatment Storage Disposal Facilities & EJSCREEN: USEPA Hazardous waste (TSDF)

Method

The method used for calculating tract scores was the CalEnviroScreen: Site Weight-Multi-Ringed Buffer Proximity Method (Faust *et al.* 2017; Walker Weiland personal communication, 2020) See Appendix A for more details.

IMPAIRED WATER BODIES

Michigan's rivers, streams, wetlands, inland lakes, and Great Lakes are each important in many ways and support a diversity of uses. The various designated uses that Michigan waters are intended to sustain provide for the vitality of its citizens and ecosystems by protecting human and ecological health and utilization of the waters. Pollutants that affect water quality, then, can have very impactful results to one or more uses, and thereby potentially impact the health of citizens, their local communities, and aquatic life.

Pollutants in Michigan surface waters can affect their ability to support various designated uses such as eating fish, providing safe drinking water, wading, swimming, fishing, and the protection of aquatic animals. In cases where these uses are impacted, such waters are considered "impaired." Information on various pollutants causing impairments helps determine the extent of environmental degradation within an area, and ultimately provides opportunities for various federal, state, and local programs to begin addressing water quality problems.

Identifying pollutant impairments to Michigan's designated uses may clarify potential impacts to human health, ability to recreate, and the quality and resiliency of local ecosystems. Because not all communities interact with, and rely on, waters in the same way, the number of identified pollutants impairing water quality may provide a helpful context in combination with other environmental effects indicators when exploring potential community-level impacts. For example, communities of color, low-income communities, and tribes generally depend on the fish, aquatic plants, and wildlife provided by nearby surface waters to a greater extent than the general population (NEJAC, 2002).

Indicator

Summed number of pollutants across all water bodies designated as impaired within the area (2018 Integrated Report Data).

Data Source

303(d) List of Impaired Water Bodies, Water Resources Division (WRD), EGLE.

Every two years, as required by the Federal Clean Water Act, the WRD assesses the quality of Michigan surface waters. This information is then provided to the USEPA as part of a biennial Water Quality and Pollution Control in Michigan Sections 303(d), 305(b), and 314 Integrated Report (Integrated Report). An important part of the Integrated Report is the list of Great Lakes, inland lakes, wetlands, streams, and rivers that do meet water quality standards, or are not expected to meet water quality standards, and are listed as impaired under Section 303(d) of the Clean Water Act. Additional information, including the recent 303(d) list, is available Michigan.gov/WaterQuality.

Method

The method used for calculating is based on CalEnviroScreen and includes:

- Data on water body type, water body assessment unit ID, and pollutant type were downloaded in Excel format and merged with GIS datasets showing the spatial representation of all water bodies, including rivers, inland lakes, great lakes bays and point locations. Assessment Unit data is now available on EGLE's open data portal: https://gis-egle.hub.arcgis.com/search
- All water bodies were identified in Michigan census tracts in the GIS software ArcGIS Pro.
- The number of pollutants listed in streams or rivers that fell within 1 kilometer (km) or 2 km of a census tract were counted. The 2 km buffer distance was applied to major rivers (>100 km in length). The 1 km buffer distance was applied to all smaller streams/rivers.
- The number of pollutants listed in lakes, bays, estuaries, or shorelines that fell within 1 km or 2 km of a census tract were counted. The 2 km buffer distance was applied to major lakes or bays greater than 25 square kilometers in size. The 2 km buffer distance was also applied to all Great Lakes assessment units. The 1 km buffer distance was applied for all other lakes/bays.

PROXIMITY TO SOLID WASTE SITES AND FACILITIES

Michigan's Solid Waste policy classifies waste as a state resource which EGLE aims to manage safely and sustainably. A key component in this effort are solid waste sites, including landfills, transfer stations, and composting facilities, or places where waste is collected, processed, or stored. Waste sources include households, industry, and commercial operations. View a map of Michigan's Type II and Type III Landfills at Michigan.gov/EGLEWaste (Under Solid Waste | Solid Waste Information).

Older or abandoned facilities and sites out of compliance with EGLE regulations may have negative impacts on the surrounding environment, creating risk of exposure for those living nearby. Methane and carbon dioxide, greenhouse gases which have been shown to contribute to climate change, can be released from such facilities for decades even after site closure (US EPA, 2011; Ofungwu and Eget, 2005). Epidemiological studies have associated negative impacts on reproductive health, increased rates of birth defects, and exposure to hydrogen sulfide which correlated with an increase in mortality and morbidity from respiratory disease with living near solid waste facilities (Roelofs et al., 2012; Palmer et al., 2005; Mataloni et al. 2016). These sites can also raise concerns of odors, vermin, and increased truck traffic and diesel pollution. These can affect quality of life and health of residents by also negatively impacting the perceived desirability of the community which can result in serious socioeconomic outcomes (Heaney et al., 2011).

Indicator

Proximity to solid waste sites and facilities (Part 115 licensed landfills, old dumpsites, and scrap tire sites).

Data Source

Michigan EGLE Part 115 Landfills, Michigan Scrap Tire Program and Old Dump Sites

Method

The method used for calculating tract scores was the CalEnviroScreen: Site Weight-Multi-Ringed Buffer Proximity Method (Faust *et al.* 2017) See Appendix A for more details. Solid Waste Sites and Facilities were additionally area weighted.

LEAD PAINT INDICATOR

This indicator reflects the percent of households in a census tract built before 1960, which have been found to be significantly more likely to contain lead-based paint than those built after 1960. Lead is a heavy metal and a neurotoxin that can accumulate in soft tissues and cause serious health complications. Lead has no known safe level of exposure for humans. While lead exposure can occur through interactions with contaminated air, water, dust, food, or consumer products, historically used lead paint is a main lead exposure pathway for many people living in the United States and the most significant pathway for children.

Despite the 1978 Consumer Product Safety Commission ban on lead-based paint, many buildings where lead paint was used still pose a significant health risk to the public. Lead may accumulate in dust indoors and chipping of exterior paint can be a source of ambient lead. Additionally, monitoring following the demolition of old buildings has been associated with increased short-term lead dust loadings (U.S. EPA, 2011). Levin et. al (2008) found that lead-based paints and contaminated dust and soil are the leading cause of lead exposure in children in the United States. Children’s hand-mouth behavior puts them at increased risk of ingesting lead from these sources.

Lead exposure is of particular concern to EJ stakeholders as it represents a key environmental health issue that may put certain demographic groups at greater risk than others (U.S. EPA, 2006, 2011). Mexican Americans and non-Hispanic Black people are significantly more likely to experience negative cardiovascular health outcomes associated with lead exposure than non-Hispanic Whites (U.S. EPA 2011). Research has also suggested that lead exposure has a greater impact on measures of intelligence for people of low socioeconomic status (U.S. EPA 2011c).

Indicator

Percent of housing built before 1960.

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2021.

Method

This indicator was developed using data on the percent of housing built before 1960 collected from the U.S. Census Bureau's American Community Survey 5-year estimates for 2015-2019. The ACS 5-year estimate is recommended by the US Census Bureau as the most reliable estimate measure of census variables for small populations. The Proximity to Lead Paint Indicator data which is mapped at the block group level by the USEPA was downloaded from the EPA EJSCREEN web site. For each census tract, the block groups within the tract were summed.

Proximity to Risk Management Plan (RMP) Sites

RMP sites refer to facilities that are required by Clean Air Act (CAA) section 112 (r) and the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA) to file risk management plans. These regulations establish a List of Regulated Substances including 72 substances known to have high acute toxicity and 60 flammable or explosive substances as well as threshold quantities (TQ) for each. Accidental releases of such hazardous substances during production, use, or transportation have resulted in evacuations, injuries and even death. Such events and a general concern for the risks of chemical accidents ultimately led to the passing of the EPCRA and the addition of section 112 (r) to the CAA, which create reporting and planning requirements for a range of facilities, the EPA, and state and local planning and response organizations.

Facilities are obligated to file risk management plans with the EPA if it maintains a quantity of any of the listed regulated substances above the TQs. Thus, these RMP sites can be highly diverse in the purpose, size, and structure of their operations as well as the make-up of the regulated substances they use. Such industrial facilities may have routine releases of residuals following pollution control measures to remove the majority of the waste stream into local air or water ways. People in surrounding areas can therefore be exposed indirectly or directly through ingestion or inhalation. However, the primary public health risks for RMP sites are accidental releases and fires or explosions. Local residents, workers, and emergency responders can suffer sever adverse health effects from such incidents.

Indicator

Proximity to facilities with Risk Management Plans.

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2021.

Method

EJSCREEN uses the count of RMP facilities within 5km, divided by distance, presented as population-weighted averages of blocks in each block group. For more information, refer to EJSCREEN Technical Documentation: www.epa.gov/ejscreen/technical-documentation-ejscreen. The Proximity to RPM Sites data which is mapped at the block group level by the USEPA was downloaded from the EPA EJSCREEN web site. For each census tract, the block groups within the tract we were summed.

WASTEWATER DISCHARGE INDICATOR

The wastewater discharge indicator describes pollutant loadings from the Discharge Monitoring Report (DMR) Loading Tool (which include NPDES DMR discharges and TRI releases) for toxic chemicals reported to the Toxics Release Inventory (TRI). This data was also treated by the Risk-Screening Environmental Indicators model, which incorporates information from TRI on the amount of toxic chemicals released, factors such as the chemical's fate and transport through the environment, relative toxicity, and potential human exposure. As such, the wastewater discharge indicator gives greater weight to releases of highly toxic chemical and to communities downstream of a discharge relative to those the same distance upstream or in the general area. Moreover, the indicator accounts for dilution within the discharge steam by including flow volume.

Water pollutants can have both adverse effects on public health and the environment. The severity of this impact depends on the concentration of pollutant in the water, the toxicity of the chemical in question, the exposure pathway, and other factors. Potential exposure pathways include swimming or other recreation in downstream waters and infiltration of drinking waters at the surface or in aquifers. According to the EPA, there are nearly 6,700 major facilities across the United States that discharge approximately 50 billion pounds of pollutants directly into the nation's streams and rivers (U.S. EPA, 2012).

Indicator

Toxicity-weighted concentrations in stream segments within an area.

Data Source

The data used to calculate this indicator were downloaded from EJSCREEN in 2021.

Method

EJSCREEN uses the toxicity-weighted concentration in stream reach segments within 500 meters of a block centroid, divided by distance in meters, presented as the population-weighted average of blocks in each block group. For more information, refer to EJSCREEN Technical Documentation: www.epa.gov/ejscreen/technical-documentation-ejscreen. The Wastewater Discharge Indicator data which is mapped at the block group level by the USEPA was downloaded from the EPA EJSCREEN web site. For each census tract, the block groups within the tract we were summed.

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Population Characteristics: Sensitive Populations Indicators

Indicator	Details	Source	Data Year
Asthma	Spatially modeled, age-adjusted rate of emergency department visits for asthma per 10,000	Michigan Hospital and Health Association. Division for Vital Records and Health Statistics, MDHHS	2016-2019
Cardiovascular Disease	Spatially modeled, age-adjusted rate of hospitalization for cardiovascular disease per 10,000	Michigan Hospital and Health Association. Division for Vital Records and Health Statistics, MDHHS	2016-2019
Low Birth Weight Infants	Percent low birth weight averaged over 2014-2019	Michigan Birth Files. Division for Vital Records and Health Statistics, MDHHS	2014-2019
Blood Lead Level	Percent of tested children with elevated (≥ 5 µg/dL) blood lead levels	MDHHS	2018-2019
Life Expectancy	Average number of years a person can expect to live	National Center for Health Statistics. United State Small-area Life Expectancy Estimates Project	2010-2015

ASTHMA

Asthma is a chronic health condition affecting the airways in the lung. These airways can become inflamed and narrowed resulting in shortness of breath, wheezing, coughing, and chest tightness. Asthma can be life threatening disease, but it can also be managed as a chronic condition. Monitoring, avoiding triggers, and access to medicines and regular medical care can significantly reduce the severity of symptoms and likelihood of requiring emergency care (Delfino et al., 1998; Grineski et al., 2010). Thus, emergency care visits to treat asthma are only a proxy for overall asthma cases in the population. However, this indicator therefore also speaks to aspects of access to care.

There is a potential for biases in utilizing this data set due to the possibility that some populations may not have access to healthcare facilities. Lower socioeconomic or rural populations may encounter monetary or transportation barriers if an asthmatic person requires emergency care. Another bias potentially inflating this indicator is the possibility that people without access to health insurance may rely more heavily on emergency departments for care.

While the exact cause of asthma is still unknown, known risk factors include a family history of asthma, exposure to environmental pollutants, and preexisting health conditions. Asthma is an important indicator of population sensitivity as the condition increases one's sensitivity to pollutants. Research has connected exposure to air pollutants such as particulate matter, ozone, nitrogen dioxide, and diesel exhaust to asthma attacks (Meng et al., 2011). Exposure to certain pesticides can also trigger symptoms among asthmatics (Hernández et al., 2011). Furthermore, asthmatic people are also predisposed to developing other respiratory diseases (Kloepfer et al., 2012). Zanobetti et al (2000) found that people with asthma were twice as likely to be hospitalized with pneumonia than people without the disease following high levels of ambient particulate pollution. Findings from Pandya et al (2002) suggest that particulate matter from diesel engines could be a disease pathway for new-onset asthma.

Indicator

Spatially modeled, age-adjusted rate of emergency department visits for asthma per 10,000 (averaged over 2016-2109).

Data Source

Data was prepared by Division for Vital Records & Health Statistics, MDHHS using the Michigan Outpatient Database and the Michigan Inpatient Database. Asthma is identified in the outpatient and inpatient discharges using ICD-10-CM code J45 as a primary discharge.

Method

- Outpatient and inpatient discharges were obtained from the Michigan Hospital & Health Association for 2016-2019. Counts of cases were calculated by census tract in cases when the census tract was provided (about 90% of the time); otherwise, the census tract was estimated from the zip code using a weighted geographic correspondence table.
- Population was purchased from PopStats, which provides census tract population for Michigan by year.
- Age-adjusted rates for asthma and cardiovascular disease were then calculated using 10-year age groups. The rates were 10,000 discharges/visits per year.
- Finally, the rates were spatially smoothed using procedures from the software program SpaceStat. Rates that remained unstable, due to low population counts or missing data were censored in the files with the number -9999.

CARDIOVASCULAR DISEASE

Heart disease describes numerous conditions caused by blocked or narrowed blood vessels such as an acute myocardial infarction (AMI), commonly known as a heart attack. Other relevant conditions include arrhythmias, congenital heart defects, coronary artery disease, and others. Heart disease causes nearly one in four deaths in the United States, making it the leading cause of death nationally. Heart attacks are the most common cardiovascular event and although the survivorship of heart attacks has increased significantly in recent years, survivors can experience profound impacts on their quality of life and long-term survival. Survivors also become highly vulnerable to future cardiovascular events.

The risk of cardiovascular mortality for survivors of heart attacks and those with heart disease is significantly higher when exposed to environmental stressors, particularly high levels of particulate matter air pollution (Bateson and Schwartz, 2004; Berglind et al., 2009; Brook et al., 2010; Chen et al., 2016). Studies have also shown long term exposure to air particulates correlates with reduced life expectancy for people with heart disease (Brook et al., 2010). Even short-term exposure has been linked to acute cardiovascular events (Pope et al., 2006; Schwartz, 1994; von Klot et al., 2009). Lifestyle risk factors such as tobacco use, poor nutrition, lack of physical activity, and excessive alcohol use can also play a role in the development of cardiovascular disease (Pope et al. 2006; Brook et al. 2010).

Indicator

Spatially modeled, age-adjusted rate of hospitalization for cardiovascular disease per 10,000 (averaged over 2016-2019).

Data Source

Data was prepared by Division for Vital Records & Health Statistics, MDHHS using the Michigan Outpatient Database and the Michigan Inpatient Database. Cardiovascular disease is identified in the outpatient and inpatient discharges using ICD-10-CM codes for diseases of the heart I00-I09, I11, I13, and I20-I51; cerebrovascular disease (stroke) I60-I69, and diseases of the arteries, arterioles, and capillaries(I70-I78); only the primary discharge code was considered.

Method

- Outpatient and inpatient discharges were obtained from the Michigan Hospital & Health Association for 2016-2019. Counts of cases were calculated by census tract in cases when the census tract was provided (about 90% of the time); otherwise, the census tract was estimated from the zip code using a weighted geographic correspondence table.
- Population was purchased from PopStats, which provides census tract population for Michigan by year.
- Age-adjusted rates for asthma and cardiovascular disease were then calculated using 10-year age groups. The rates were 10,000 discharges/visits per year.
- Finally, the rates were spatially smoothed using procedures from the software program SpaceStat. Rates that remained unstable, due to low population counts or missing data were censored in the files with the number -9999.

LOW BIRTH WEIGHT INFANTS

Low Birth Weight (LBW) refers to newborns weighing less than 5.5 pounds or 2,500 grams. LBW is associated with increased risk for developing chronic health conditions such as asthma, coronary heart disease, and type 2 diabetes (Barker et al., 2002; Lu and Halfon, 2003; McGauhey et al., 1990; Nepomnyaschy and Reichman, 2005).

LBW is often a result of a premature birth, though full-term infants can also be LBW due to restricted growth during pregnancy. Social risk factors include stress, maternal smoking, lower socioeconomic status, lack of prenatal care and proper nutrition (Ghosh et al., 2012; Harley et al., 2011; Laurent et al., 2013, Westergaard et al., 2017). Environmental risk factors include exposures to lead, toxic air contaminants, traffic pollution, pesticides, and polychlorinated biphenyls (PCBs). Additionally, the health conditions linked with LBW can predispose the child's sensitivity to and mortality associated with environmental stressors (Bateson and Schwartz, 2004; Basu and Samet, 2002). For example, asthma attacks, hospitalizations, and deaths are made more likely for LBW children who are exposed to air pollution. Research has also provided evidence that LBW is more common among Black women than Hispanic and non-Hispanic White women even when controlling for social risk factors (Lu and Halfon, 2003).

Indicator

Percent low birth weight averaged over 2014-2019

Data Source

Michigan Birth Files. Division for Vital Records & Health Statistics, MDHHS.

Method

- The low birth weight (LBW) rate was calculated from Michigan birth records as the percent of live, singleton births during the 2014-2019 period weighing less than 2,500 grams.
- Multiple births (non-singletons) and births with an improbable combination of gestational age and birth weight were excluded (Alexander, 1996). Out-of-state births, and births with no known residential address (including P.O. boxes) were also excluded. These exclusions lead to a lower statewide LBW rate than that reported by other organizations who do not apply this criterion.
- Births were geocoded based on the mother's residential address at the time of birth. A small number (less than 1%) of addresses could not be geocoded and were excluded.
- Estimates derived from places with few births are considered unreliable because they often produce extreme values much higher or lower than expected and can vary greatly from year to year. For this reason, census tracts with fewer than 50 live births for seven years were excluded. The average low birth weight rate was estimated using five years of data (2014-2019) in order to minimize the number of excluded census tracts.
- Each census tract was assigned a percentile based on its relative ranking of spatially modeled LBW compared to all other tracts.

Blood Lead Level

According to the CDC's Advisory Committee on Childhood Lead Poisoning Prevention, there is no safe level of lead in the blood. (CDC, 2012) Young children are particularly vulnerable to lead exposure. They tend to put their hands, toys, and other items into their mouths, increasing their chances of ingesting lead (CDC, 2013; CDC, 2014). Due to children's smaller size, the same amount of lead will have more impact in a child than in an adult (CDC, 2014). The effects of lead on the developing child can be devastating since the central nervous system is undergoing a period of rapid and critical growth (CDC, 2012; CDC, 2013; AAP, 2016; Amato et. al, 2012). In children, exposure to lead has been linked to:

- Learning and behavioral issues, including ADHD and hyperactivity
- Lower IQ
- Slowed growth and development
- Hearing and speech difficulties
- Anemia

Lead Sources

Lead enters the body through breathing in, eating, or drinking lead. The most common source of lead is from deteriorating lead paint in homes built before the lead paint ban in 1978. (CDC, 2012; AAP, 2016; Laidlaw et. al, 2016; NCHH, 2008; Stewart et. al, 2014; Spanier et. al, 2013). Deteriorating paint may be peeling, chipping, blistering, flaking, worn, chalking, cracking, or otherwise becoming separated from the painted surface. This creates hazardous paint chips and dust that can settle on windowsills, floors, porches, and in the soil around the outside of a home. Repair and renovation of these homes can create hazardous lead dust if lead-safe work practices are not followed (AAP, 2016; NCHH, 2008; Spanier et. al, 2013).

Besides deteriorating paint and leaded plumbing and pipes, there are other visible and invisible sources of lead in and around the home, (CDC, 2013; Laidlaw et. al, 2016; NCHH, 2008; Stewart et. al, 2014; Spanier et. al, 2013) including:

- Soil (dirt) on properties near high-traffic streets and highways, from leaded gasoline exhaust
- Soil on former industrial sites like mines or smelters (brownfields)
- Other plumbing fixtures and solder
- Pottery with glazes containing lead
- Hobby supplies, including lead buckshot, fishing weights, and lead cane for stained glass
- Imported cosmetics
- Imported toys, jewelry, or furniture with lead paint or parts
- Imported sauces, spices, candy, health supplements, folk remedies, and ayurvedic medicines (CDC, 2014; White et. al, 2016).

The chances of children being in contact with (exposed to) lead are higher for those living in older homes and in poverty; it is also more common in the children of some ethnic and racial groups (CDC, 2014; White et. al, 2016; CDC, 1994). Michigan's urban areas tend to have aging homes, aging plumbing, and substandard living conditions, potentially increasing the risk of lead exposure for those that live in those areas.

Indicator

Percent of tested children under age 6 with elevated (≥ 5 μg/dL) blood lead levels (2018 and 2019 combined).

Data Source

MDHHS Childhood Lead Poisoning Prevention Program (CLPPP) blood lead data tables, MDHHS Data warehouse. Data for this analysis was pulled from the CLPPP Monthly Executive Dataset for 8/30/2020 and is current as of 9/28/2020

Method

Blood lead test results are reported to CLPPP by testing laboratories. Each result is processed through the Michigan Childhood Lead Poisoning Surveillance (MICLPS) application. Test results are reported with patient information including address which is geocoded using the State Center for Shared Services SAP address validator. Approximately 98-99% of test results reported since 2018 have census tract data assigned using this process. The blood lead results are sent to the MDHHS Data Warehouse where each record is assigned a Master Person Index (MPI) identifier that is used to link individuals with multiple tests.

CLPPP Epidemiologists pulled the 2018 and 2019 data for children less than 6 and performed deduplication to report one test result per child over the two years. This retains the highest Venous test result for the time-period and if no venous result, the highest capillary. If the only test result had an unknown sample type, that result was retained. Test results were assigned elevated blood lead level (EBLL) status using the standard CLPPP definition of 4.5 μg/dL.

The data was then aggregated with using the address that was reported with the retained blood lead test result. Results that failed to geocode were omitted from this analysis. Counts of total children tested, total EBLL and Percent EBLL were aggregated using SAS. Percent EBLL was calculated by dividing the total EBLL by the total number of children tested in each census tract. Due to Public Health Administration policy, counts between 1-5 and corresponding percentages are required to be suppressed to protect patient privacy. Unsuppressed data was provided to the EJ Research and Data Workgroup to be used in the algorithm, but only suppressed versions can be included for public use.

LIFE EXPECTANCY

Life expectancy refers to the average number of years a person can expect to live from birth if the mortality patterns that exist during the original estimate persist over their lifetime. Life expectancy serves as an indicator of overall public health as it speaks to the cumulative impact of socioeconomic and environmental factors, behavioral and genetic risk factors, and access and quality of health care. While the principles of environmental justice prescribe that everyone should be able to live a long and healthy life, many inequities in these factors create disparities in the longevity of community members.

Research has suggested environmental quality is positively correlated with longevity; lack of access to safe drinking water, sufficient nutrition, and public health expenditures was linked with a shorter life expectancy at birth (Gulis, 2000). Correia et. al (2013) found a similar trend between air pollution and life expectancy, where results demonstrated that air pollution control efforts which decreased ambient particulate concentrations corresponded with an increase in mean life expectancy.

Longevity is also a function of geographical location, such that zip code is a strong predictor of both health and life expectancy in the United States (Bullard et. al, 2011; LeCounte et. al,2017). Studies suggest that this is mainly attributed to the differences in the socioeconomic and environmental conditions in which children grow up (LeCounte et. al, 2017). Household income, which is often similar across a zip code, has a significant relationship with life expectancy. Chetty et. al (2016) found that higher income correlated with greater longevity, and that over a thirteen-year period between 2001 and 2014 this trend was only intensifying.

Other social factors that may influence the average age a person can expect to live are gender and race. It has been a long-term trend in the United States that persons identifying as female generally live longer than those who identify as male. In 2018, females of all origins could expect to live an average of 81.2 years from birth, while males of all origins could expect to live 5 years less; this trend persists within racial and ethnic groups (Hispanic, non-Hispanic White, and non-Hispanic Black) as well (NCHS, 2018). Although the exact cause for the gender disparity in mortality is not known, studies suggest that the social acceptability of behavioral risk factors in men such as usage of guns, alcohol, and cigarettes, acting unafraid, and working hazardous jobs may contribute (Waldron and Johnson, 1976). In the same year, people of Hispanic origins in the U.S. could expect to live 81.8 years from birth, where non-Hispanic Whites and Black people could expect to live 78.6 and 74.7 years respectively (Arias and Xu, 2020).

Notably, there have been significant and disproportionate reductions in the estimated life expectancy for Black and Hispanic/Latino populations as a result of the COVID-19 pandemic (Andrasfay and Goldman, 2021).

Indicator

Average number of years a person can expect to live (estimated average from 2010-2015)

Data Source

National Center for Health Statistics. U.S. Small-Area Life Expectancy Estimates Project (USALEEP): National Center for Health Statistics. 2018. Available at www.cdc.gov/nchs/nvss/usaleep/usaleep.html.

Method

The methodology developed to produce the life expectancy estimates by U.S. census tract consist of a combination or standard demographic techniques and statistical modeling. For more information, refer to U.S Small-area Life Expectancy Estimates Project: Methodology and Results Summary: www.cdc.gov/nchs/data/series/sr_02/sr02_181.pdf

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Population Characteristics: Socioeconomic Factor Indicators

Indicator	Details	Source	Data Year
Low Income Population	Percent of population living below two times the federal poverty level	U.S. Census Bureau's ACS	5-year estimate, 2015-2019
Black, Indigenous, People of Color Population	The sum of all race/ethnicity categories except White/Non-Hispanic. It includes Black, American Indian/Alaskan Native, Asian, Native Hawaiian-Other Pacific Islander and two or more races	American Community Survey (ACS) through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Educational Attainment	Percent of population over age of 25 with less than a high school education	ACS through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Linguistic Isolation	Percent limited English-speaking households	ACS through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Population Under Age 5	Percent of population under age 5	ACS through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Population Over Age 64	Percent of population over age 64	ACS through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Unemployment	Percent of the population over the age of 16 that is unemployed and eligible for the labor force. Excludes retirees, students, homemakers, and institutionalized persons	ACS through ESRI Living Atlas of the World	5-year estimate, 2015-2019
Housing Burden	Percent of households spending over 30% of income on housing costs	U.S. Census Bureau's ACS	5-year estimate, 2014-2018

LOW INCOME POPULATION

The US Census Bureau sets the Federal Poverty Level, a measure of income adjusted for the size of a household, annually. The low-income population indicator in MiEJScreen refers to the percent of the population living below double the federal poverty level. Income is a social determinant of health as it can determine key risk factors such as housing status and location, educational attainment, access to health insurance, and mental health status. Several studies suggest low-income communities are more likely than wealthier communities to experience higher rates of chronic diseases (Marmot & Wilkinson, 2006). When faced with environmental risk factors, communities with more low-income households have also been shown to have lower resilience and greater vulnerability (Cakmak, Dales, & Judek, 2006, Forastiere et al., 2006; Marmot & Wilkinson, 2006; O'Neill et al., 2003, Yi, Kim, & Ha 2009; Zeka, Melly, & Schwartz, 2008).

Additionally, living in poverty creates chronic stress for individuals, modifying their biological susceptibility or extrinsic vulnerabilities (O'Neill et al., 2003).

Indicator

Percent of population living below two times the federal poverty level. (5-year estimate, 2015-2019)

Data Source

American Community Survey, US Census Bureau.

Method

This indicator uses data on the percent of the population living below 185 percent of the federal poverty level from the U.S. Census Bureau's American Community Survey for 2015–2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

BLACK, INDIGENOUS, PEOPLE OF COLOR POPULATION

It is well established that non-White racial and ethnic groups are disproportionately affected by environmental risk factors (Bell and Dominici, 2008; Cushing et al., 2015; Kravitz-Wirtz et al., 2016; Balazs and Ray, 2014). As mentioned in other indicator descriptions of this report, Superfund-NPL sites and other hazardous sites are more likely to be found near communities of color (Pollock and Vittas, 1995). Non-White populations are not only more likely to live near pollution, but also more likely to experience negative health impacts associated with exposure. Outcomes such as heart disease, mortality, premature birth, low birth weight, and miscarriage mainly associated with air pollution are more prevalent in these populations, particularly Black populations (Bell et al., 2007; DOH, 2013; Green et al., 2004; Lu and Halfon, 2003; Ponce et al., 2005; Smith et al., 2005). The connection between racial disparities in the prevalence of asthma and air pollution has been widely studied.

Ultimately, the causes of racial and ethnic disparities in health status associated with environmental pollutants are still not completely understood and very complex. However, the experience of racism in the form of segregation and reduced access to healthcare, social goods and resources acts as a barrier to health and well-being (Pascoe and Smart Richman, 2009; Williams and Mohammed, 2009). Additionally, research has implicated chronic stress due to the experience of racism for the negative health outcomes of minority groups (Paradies, 2006).

Indicator

The sum of all race/ethnicity categories except White/Non-Hispanic. It includes Black, American Indian/Alaskan Native, Asian, Native Hawaiian-Other Pacific Islander and two or more races. (5-year estimate, 2015-2019)

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator is a sum of all race/ethnicity categories except White/Non-Hispanic. It includes Black, American Indian/Alaskan Native, Asian, Native Hawaiian-Other Pacific Islander and two or more races from the U.S. Census Bureau's American Community Survey for 2015–2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

EDUCATIONAL ATTAINMENT

Educational attainment is an important element of socioeconomic status and a social determinant of health. Numerous studies associate educational attainment with susceptibility to the health impacts of environmental pollutants such as air pollution (Cakmak, Dales, & Judek, 2006; Krewski et al., 2003). Additionally, studies found higher educational attainment to be associated with higher life expectancy and reduction of risks for diseases associated with aging (Adler et al., 2013; Hummer & Hernandez, 2013).

The ways in which lower educational attainment can decrease health status are not completely understood, but may include economic hardship, stress, fewer occupational opportunities, lack of social support, and reduced access to health-protective resources such as medical care, prevention and wellness initiatives, and nutritious food. A review of studies tying social stressors with the effects of chemical exposures on health found that level of education was related to mortality and incidence of asthma and respiratory diseases from exposure to particulate air pollution and sulfur dioxide (Lewis et al., 2011).

Indicator

Percent of population over age of 25 with less than a high school education.
(5-year estimate, 2015-2019)

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator was developed using data on the percent of population over age 25 with less than a high school education collected from the U.S. Census Bureau's American Community Survey 5-year estimates for 2015-2019. The ACS 5-year estimate is recommended by the US Census Bureau as the most reliable estimate measure of census variables for small populations.

LINGUISTIC ISOLATION

Linguistic isolation is defined by the US Census Bureau as living in a household in which all members 14 years and older speak a non-English language and also speak English less than "very well." The percent of these households in a census tract is represented in the MiEJScreen linguistic isolation indicator. Michigan is home to many people who speak languages other than English, mainly Spanish, Arabic, and Chinese.

In the US, people with limited English can experience language as a barrier to accessing health care, including mental health care, and may be unable to participate in public health surveillance studies (Link et al., 2006; Sentell, Shumway & Snowden, 2007; Shi, Lebru & Tsai, 2009).

Linguistic isolation may also affect a community's capacity for civic engagement affecting environmental policies, which can lead to environmental health disparities (Pastor Jr., Morello-Frosch & Sadd, 2010). Lack of proficiency in English often results in racial discrimination, and both language difficulties and discrimination are associated with stress, low socioeconomic status, and reduced quality of life (Gee and Ponce, 2010).

Indicator

Percent limited English-speaking households. (5-year estimate, 2015-2019)

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator was developed using census tract-level data on the percent of limited English-speaking households from the U.S. Census Bureau's American Community Survey for 2015– 2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate indicator of census variables at the census tract level of geography.

POPULATION UNDER AGE 5

Children have an increased susceptibility to environmental stressors relative to adults; this is due to biological factors such as smaller airways, lower body weight, and higher metabolism. Children's higher metabolism is a function of their proportionately greater skin surface area relative to their bodyweight, providing more surfaces by which heat can escape. Thus, a higher metabolism is necessary to maintain body temperature and growth. Fueling this higher metabolism is a greater oxygen and food demand which can result in greater exposure to air and food contaminants respectively (Hubal et al., 2000). High breathing rates have been linked to increased particle deposition in children's relatively small airways, creating an increased susceptibility to developing asthma. Moreover, children and particularly newborns have skin that is softer and more readily infiltrated by pollutants than adults. Once a layer of fat develops underneath the skin at around 2 to 3 months old, infants up to 36 months old may have higher susceptibility to fat-soluble chemicals than adults as percent body fat generally decreases with age (OEHHA, 2001; Hubal et al., 2000). Importantly, once contaminants are absorbed by a child, their immature kidneys are unable to filter them from the body as effectively as children over 5 and adults (Sly and Flack, 2008).

This increased susceptibility can also be a function of behavioral risks specific to childhood. Research has shown that children under two years old have the greatest exposure to lead in soils and household dust due to hand-to-mouth contact (Bellinger, 2004; Howarth, 2012) Children are also more biologically susceptible to low-level lead exposures (Canfield et al., 2003).

Indicator

Percent of population under age 5 (2015-2019).

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator uses data on the percent of the population under the age of 5 from the U.S. Census Bureau's American Community Survey for 2015–2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

Population over Age 65

Elderly populations also have an increased sensitivity to exposure to environmental stressors compared to the general population. Biological functions such as metabolism, distribution, and excretion can change with age. Generally, people over the age of 65 experience reduced metabolic rates that can decrease blood flow in the body; this can also reduce their capacity to expel harmful chemicals (Pederson 1997). Other reductions in total body water, lean body mass, kidney function, and some blood proteins may also contribute to an increase susceptibility to pollutants (Risher et al., 2010).

Elder people are also more likely to have heart disease, which is utilized as an indicator of sensitive populations for this tool, than the general population. Such conditions can increase the susceptibility of people over 65 to the effects of particulate air pollution exposure and decrease heart rate and oxygen saturation (Adler, 2003). Global research has shown that the elderly people face an increased risk of being hospitalized for strokes, heart attacks, atherosclerosis, and pulmonary heart disease when exposed to high concentrations of air pollution (Hong et al., 2002). The increased prevalence of stroke has been correlated with increased concentrations of pollutants like carbon monoxide, sulfur dioxide, and nitrogen oxide (Adler, 2003). Shumake et al. (2013) found in a review of research on pollution exposure and age than the elderly are generally more susceptible to the health impacts of air pollution. Risk of death for people over 65 can increase significantly with even small increases in PM2.5 and ozone exposure (Di et al., 2017).

Indicator

Percent of population over the age of 65 (2015-2019).

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator uses data on the percent of the population over the age of 65 from the U.S. Census Bureau's American Community Survey for 2015–2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

Unemployment

While unemployment is often used as a measure of health for the economy, it can also signal health outcomes for the population. Unemployment is representative of poor health and vulnerability to environmental burden as lack of employment and corresponding low income can act as risk factors within the population (Athar et al., 2013; Davis et al., 2010; Dragano et al., 2008; Hafkamp-de Groen et al., 2013; Tapia Granados et al., 2014; Turner, 1995). For example, unemployed and low-income peoples may only find affordable housing in neighborhoods that are highly polluted. Moreover, research has indicated that chronic unemployment may increase risk of developing aging-associated diseases (Ala-Mursula et al., 2013). Dragano et al. (2008) found that areas with high unemployment rates are correlated with higher rates of coronary heart disease. Being unemployed can also be a major source of stress, which research and community members suggest contributes to poor environmental health (deFur et al., 2007; Premji et al., 2007).

The COVID-19 pandemic has brought new meaning to unemployment as an indicator of population health. In the wake of lockdowns and stay-at-home orders as public health measures and the coinciding economic recession, millions of working adults in the United States lost their jobs. However, some populations were more likely to maintain employment than others. Race and gender disparities in the labor market are not new to the United States, where racial minorities and women often experience discrimination in hiring practices, unfair wages, and other barriers in the workplace; the same disparities can be seen in the distribution of pandemic-induced job losses such that women and people of color were more likely to become unemployed than their male and white counterparts (Gezici and Ozay, 2020).

Indicator

Percent of the population over the age of 16 that is unemployed and eligible for the labor force. Excludes retirees, students, homemakers, institutionalized persons. (5-year estimate, 2015-2019)

Data Source

American Community Survey, US Census Bureau, through ESRI Living Atlas of the World.

Method

This indicator uses the percent of the population over the age of 16 that is unemployed and eligible for the labor force from the U.S. Census Bureau's American Community Survey for 2015– 2019. This indicator excludes retirees, students, homemakers, institutionalized persons except prisoners, those not looking for work and military personnel on active duty. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables at the census tract level of geography.

HOUSING BURDEN

Having continued access to a stable housing situation is an important prerequisite to improved health, educational, and economic outcomes for households. The ability of a household to afford their home is an important determinant of housing security (Cox et al, 2017; Cox et al, 2019). While there are other indicators that can be employed to measure this concept, a statistic that has received broad acceptance is shelter overburden (Cox et al, 2017). It measures the percentage of households that pay more than 30% of their incomes on shelter costs. High values indicate areas where many resident households struggle to pay for their shelter.

Indicator

Percent of households paying more the 30% of their income on shelter costs. (5-year estimate, 2014-2018)

Data Source

American Community Survey, US Census Bureau.

Method

Data for this statistic come from the American Community Survey and are measured at the census tract level. The Bureau of the Census uses two pieces of information to calculate this measure. The first is household income, defined by adding all of the incomes of household members from all sources (wages, Social Security, retirement funds, etc.). The second is the amount of money spent on shelter costs by each household. These vary between renters and owners; they are inclusive of contract rents and utility costs for the former, while owners' costs derive from mortgage principal and interest, insurance, utilities, taxes, and any other cost that must be met in order to maintain ownership of their home. The percentage of shelter burden is calculated from this data, as is the percentage of a tract's households that pay more than 30% of their income on shelter costs.

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APPENDIX A

Site Scoring Using the CalEnviroScreen: Site Weight-Multi-Ringed Buffer Proximity Method

For most of the Environmental Effects indicators and sub layers [Cleanup Sites Proximity, Solid Waste Sites Proximity, and Hazardous Waste Generators and Facilities (TSD and TSDF facilities)] the CalEnviroScreen Site Weight-Multi-Ringed Buffer Proximity method for applying site weights and proximity was used (Faust *et al*. 2017; Walker Weiland personal communication, 2020).

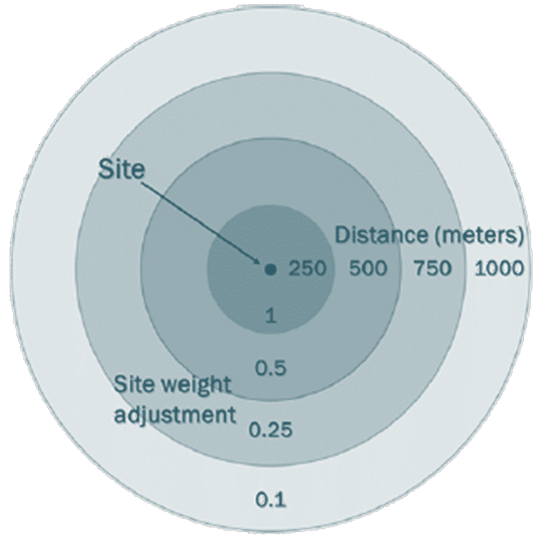
These environmental effects sites were scored based on a site weight and a proximity to populated census blocks. Most EGLE environmental effects datasets do not have a site hazard or site status, so in most cases the site weight was based on a scale of 0-10 with a single value assigned for all of the sites of that type based on a potential relative risk of that type of site compared to other types of sites. For instance, a Superfund-NPL site is generally assumed be a higher potential relative risk than a leaking underground storage tank site (Faust et al. 2017, p. 67).

The site proximity to populated census blocks is based upon, in most cases, a single latitude, longitude point location for a given site. The exception was the old dump sites where the input data were polygons. A limitation with the data is that a single point location for a site does not adequately represent the size of the site, the potential risks, impacts, or unknowns at the site.

Multi-ring buffers consisting of four (4) increasing further rings were made around each site or polygon. The width of each ring in most cases followed the CalEnviroScreen methodology of 0-250m, 250-500m, 500-750m and 750-1000m which they used for all sites regardless of the general size of the site or potential risk. It was felt that was more appropriate to use different width buffer distances based on whether in general a type of site was small, for example leaking underground storage tank sites or large, for example, Superfund-NPL sites or whether a type site had greater potential impact. Wider buffer rings were used for Superfund-NPL Sites and Hazardous Waste Generators and Facilities due to larger footprints and potential greater risks compared to other types of sites.

The site weights for all sites were adjusted based on the distance they fell from populated census blocks. Site weights were adjusted by multiplying the site weight by the multiplication factor for each buffer ring from the nearest populated census blocks within a given tract. A multiplication factor of 1 was used for the inner buffer ring; 0.5 for the 2nd buffer ring; 0.25 for the 3rd buffer ring and 0.1 for the outer buffer ring. Populated census blocks outside the outer extent of the outer ring buffer were excluded from the analysis. This effectively lessens the site weight with increasing further distance away from the site.

For a given indicator, the proximity weighted scores were summed for each census tract whether the site and its 4 multi-ringed proximity buffers were fully within the tract or partially within the tract. In some cases, individual sites and their 4 ringed buffers were all within a given tract so the total score from of the 4 rings would be added together to get the total for that tract. In other cases, a site and its buffers are near the border of 2 or more tracts. In that case, only the portions of the buffer that overlap into a given tract were added to the total. In many cases, there are overlapping buffers from several nearby sites. All the buffers or buffer portions were summed for each tract. For each indicator or sub-indicator, the summed census tract scores were ordered and assigned percentiles. Percentiles for indicators with sub-indicators were calculated by taking the sum of the sub indicator percentiles.



Graphic from Faust et al. 2017

Indicator Name	Sub Layers	Site Weight	Multiplication Factors	Multi-Ringed Buffers
Proximity to Solid Waste Sites and Facilities	Part 115 Landfills	8	1, 0.5, 0.25, 0.1	0-500m, 500-1000m, 1000-1500 and 1500-2000m
	Old Dump Sites	1.5	1, 0.5, 0.25, 0.1	0-250m, 250-500m, 500-750m and 750-1000m
	Scrap Tire Sites	4	1, 0.5, 0.25, 0.1	0-250m, 250-500m, 500-750m and 750-1000m
Proximity to Hazardous Waste Facilities & Large Quantity Generators	Part 111 Treatment and Storage Disposal Facilities and EPA Hazardous Waste Sites	5	1, 0.5, 0.25, 0.1	0-1000m, 1000-2000m, 2000-3500m and 3500-5000m
Proximity to Cleanup Sites	Part 201 Sites	5	1, 0.5, 0.25, 0.1	0-250m, 250-500m, 500-750m and 750-1000m
	Part 213 LUST Open & Closed Sites	3	1, 0.5, 0.25, 0.1	0-250m, 250-500m, 500-750m and 750-1000m
	Superfund-NPL Sites	10	1, 0.5, 0.25, 0.1	0-1000m, 1000-2000m, 2000-3500m and 3500-5000m