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# Utilization of MD EJSCREEN to Assess Health Outcomes in Baltimore, Maryland

Vivek Ravichandran, Jan-Michael Archer, Lalitha Aiyar, Julia Thompson, Max Teirstein, Ashvi Shah, Alexander Rah, and Sacoby M. Wilson

## ABSTRACT

Many industrialized communities in Baltimore, Maryland, lack information about the levels of air pollution, environmental hazards, or related health statistics in their neighborhoods. This gap prompted the development and utilization of the Maryland (MD) Environmental Justice Screening (EJSCREEN) tool, to determine the correlation of the overall MD EJSCORE and existing demographic and environmental MD EJSCREEN indicators, with selected health outcomes in Baltimore. The tool assesses environmental justice risks similar to the U.S. Environmental Protection Agency's (US EPA) EJSCREEN tool and California's tool, CalEnviroScreen 3.0. Specifically, we focused on life expectancy, adequate birth weight, and all-cause mortality present in the Baltimore Neighborhood Indicators Alliance (BNIA) 2017 dataset. Overall, we observed a moderate-to-strong relationship between fine particulate matter (PM<sub>2.5</sub>) and MD EJSCORE percentiles with the three health outcomes. Individually, MD EJSCORE is a statistically significant parameter toward estimating health outcomes in Baltimore. This cements MD EJSCREEN as an effective tool in capturing the intersectionality between environmental burden, vulnerable population, and health disparities. Based on these findings, Maryland must adopt standards, such as restricting permits for polluting facilities, encouraging uptake of electric vehicles, and promoting clean energy to ameliorate air quality in disadvantaged communities, particularly in Baltimore.

**Keywords:** children and the environment, health disparities, environmental hazards

## INTRODUCTION

Environmental Justice (EJ) is the fair treatment of people regardless of their race, income, and culture concerning the development, implementation, and enforcement of environmental laws, regulations, and policies and their meaningful involvement in the decision-making processes of the government.<sup>1</sup> In the United States, and more granularly in Baltimore, Maryland, low-income populations and communities of color are disproportionately burdened by environmental hazards and consequently health disparities

Vivek Ravichandran is a Doctoral Candidate at Maryland Institute for Applied Environmental Health, School of Public Health, University of Maryland-College Park, College Park, Maryland, USA. Jan-Michael Archer is a Doctoral Candidate at Maryland Institute for Applied Environmental Health, School of Public Health, University of Maryland-College Park, College Park, Maryland, USA. Lalitha Aiyar is an Undergraduate Student at G.W.C. Whiting School of Engineering, Johns Hopkins University, Baltimore, Maryland, USA. Julia Thompson is a Research Scientist at School of Medicine, Yale University, New Haven, Connecticut, USA. Max Teirstein is an Undergraduate Student at Department of Political Science, Yale University, New Haven, Connecticut, USA. Ashvi Shah is a High School Intern at Maryland Institute for Applied Environmental Health, School of Public Health, University of Maryland-College Park, College Park, Maryland, USA. Alexander Rah is in Maryland Institute for Applied Environmental Health, School of Public Health, University of Maryland-College Park, College Park, Maryland, USA. Sacoby M. Wilson is in Maryland Institute for Applied Environmental Health, School of Public Health, University of Maryland-College Park, College Park, Maryland, USA.

<sup>1</sup>EPA (2021) Learn about Environmental Justice. <<https://www.epa.gov/environmentaljustice/learn-about-environmental-justice>>

owing to institutionalized racism and discriminatory practices in zoning, locally unwanted land use (LULUs), community development, redlining, and local investment.<sup>2</sup> Residents of Baltimore, Maryland, currently lack information about the levels of air pollution, environmental hazards, or related health statistics in their neighborhoods. This gap prompted the development and utilization of user-friendly and interactive environmental justice screening and mapping (EJSM) tools. It is imperative to further identify relationships between environmental hazards and health effects in Baltimore, and to bolster the use, availability, and information provided in such EJSM tools.

#### *Racial and economic segregation in Baltimore city*

The Baltimore Segregation Law of 1910 continues to shape the racial inequalities faced by the city's Black communities to this day.<sup>3</sup> The legacy of racist zoning and land-use planning policies in Baltimore have given rise to a hypersegregated "black butterfly" spatial distribution, whereby predominantly African American communities occupy unfavorable real estate accompanied by higher rates of poverty, crime, and food deserts compared to White neighborhoods.<sup>4</sup> The effects of redlining and socio-spatial exclusion practices contribute toward existing economic segregation seen in Baltimore.<sup>5</sup> The political economy theory suggests economic segregation reduces the educational attainment of low-income children owing to reduced expenditure on education.<sup>6</sup> Over 50% of children residing within inner Baltimore live under the federal poverty line and half withdraw from school by the age of 16.<sup>7</sup> In addition, research has shown that living in low-income, segregated neighborhoods, which are majority Black, may negatively affect child development and family well-being.<sup>7</sup> These populations are more likely to remain in these neighborhoods than

their non-Black counterparts.<sup>8,9</sup> Further studies conducted in Baltimore have pinpointed race as the most prominent indicator for proximity to Toxic Release Inventory (TRI) facilities, suggesting the role of residential and occupational segregation.<sup>10</sup>

#### *Environmental justice concerns in Baltimore*

Baltimore, Maryland, is home to numerous major and minor air pollution sources, both stationary and mobile, which have historically contributed to its nonattainment of National Ambient Air Quality Standards.<sup>11,12</sup> A Baltimore spatial study found that tracts with higher proportions of non-White and low-income residents were more likely to be closer to TRI facilities, while also being medically underinsured, presenting a "double disparity."<sup>13</sup> Another Baltimore study identified socioeconomic disparities in the location of state-funded programmatic wetlands projects, resulting in contaminated drinking water attributed to local pollution sources and agricultural land runoff.<sup>14</sup> A study assessing park distribution in Baltimore found that a higher proportion of African Americans have access to parks within walking distance than White Americans<sup>15</sup>; however, White Americans had access to more acreage and less congested parks. A study assessing brownfields in Baltimore found that those living proximal to more brownfields experienced statistically higher cancer mortality rates, lung cancer prevalence, and respiratory disease.<sup>16</sup> A similarly

<sup>8</sup>Kellee White, and Luisa N. Borrell. "Racial/Ethnic Residential Segregation: Framing the Context of Health Risk and Health Disparities." *Health & Place* 17, no. 2 (2011): 438–448.

<sup>9</sup>White, Kellee, Jennifer S. Haas, and David R. Williams. "Elucidating the Role of Place in Health Care Disparities: The Example of Racial/Ethnic Residential Segregation." *Health Services Research* 47, no. 3pt2 (2012): 1278–1299.

<sup>10</sup>Christopher G. Boone. "An Assessment and Explanation of Environmental Inequity in Baltimore." *Urban Geography* 23, no. 6 (2002): 581–595.

<sup>11</sup>Simon, Heather, Luke C. Valin, Kirk R. Baker, Barron H. Henderson, James H. Crawford, Sally E. Pusede, James T. Kelly et al. "Characterizing CO and NO<sub>y</sub> Sources and Relative Ambient Ratios in the Baltimore Area Using Ambient Measurements and Source Attribution Modeling." *Journal of Geophysical Research: Atmospheres* 123, no. 6 (2018): 3304–3320.

<sup>12</sup>Yazan Hasan. "Environmental Justice in South Baltimore: The Intersectionality Of Poverty, Race, And Environment." (2022).

<sup>13</sup>Sacoby Wilson, Hongmei Zhang, Chengsheng Jiang, Kristen Burwell, Rebecca Rehr, Rianna Murray, Laura Dalemarré, and Charles Naney. "Being Overburdened and Medically Underserved: Assessment of this Double Disparity for Populations in the state of Maryland." *Environmental Health* 13, no. 1 (2014): 1–12.

<sup>14</sup>Matthew Dernoga, Sacoby Wilson, Chengsheng Jiang, and Fred Tutman. "Environmental Justice Disparities in Maryland's Watershed Restoration Programs." *Environmental Science & Policy* 45 (2015): 67–78.

<sup>15</sup>Christopher G. Boone, Geoffrey L. Buckley, J. Morgan Grove, and Chona Sister. "Parks and People: An Environmental Justice Inquiry in Baltimore, Maryland." *Annals of the Association of American Geographers* 99, no. 4 (2009): 767–787.

<sup>16</sup>Jonathan Hall, Isabel Shargo, Niya Khanjar, Jianna Howard, Laura Schmidt, Ashley Deng, Camryn Edwards, Isabelle Berman, Joseph Galarraga, and Sacoby Wilson. "Proximity of Urban Farms to Hazards With and Without Heavy Metal Contamination in Baltimore, Maryland." *Environmental Justice* 14, no. 1 (2021): 56–69.

<sup>2</sup>Isabelle Anguelovski. "From Toxic Sites to Parks as (Green) LULUs? New Challenges of Inequity, Privilege, Gentrification, and Exclusion for Urban Environmental Justice." *Journal of planning literature* 31, no. 1 (2016): 23–36.

<sup>3</sup>Morgan Grove, Laura Ogden, Steward Pickett, Chris Boone, Geoff Buckley, Dexter H. Locke, Charlie Lord, and Billy Hall. "The Legacy Effect: Understanding How Segregation and Environmental Injustice Unfold Over Time in Baltimore." *Annals of the American Association of Geographers* 108, no. 2 (2018): 524–537.

<sup>4</sup>Lawrence Brown. *The Black Butterfly: The Harmful Politics of Race and Space in America*. Baltimore, MD: John Hopkins University Press, 2021.

<sup>5</sup>Christopher J. Schell, Karen Dyson, Tracy L. Fuentes, Simone Des Roches, Nyeema C. Harris, Danica Sterud Miller, Cleo A. Woelfle-Erskine, and Max R. Lambert. "The ecological and Evolutionary Consequences of Systemic Racism in Urban Environments." *Science* 369, no. 6510 (2020): eaay4497.

<sup>6</sup>Susan E. Mayer. "How Economic Segregation Affects Children's Educational Attainment." *Social Forces* 81, no. 1 (2002): 153–176.

<sup>7</sup>Jo Ensign, and Joel Gittelsohn. "Health and Access to Care: Perspectives of Homeless Youth in Baltimore City, USA." *Social Science & Medicine* 47, no. 12 (1998): 2087–2099.

situated urban farm study in Baltimore found that majority African American and low-income census tracts are disproportionately situated near brownfields, placing them at increased exposure to hazardous substances and risk of injury owing to compromised infrastructure.<sup>17</sup> Further studies assessed stormwater runoff and mosquito presence in Baltimore, citing the creation of artificial containers (e.g., garbage cans) that led to high mosquito density in low-income communities.<sup>18,19,20,21</sup>

#### *Differential exposure to lead in Baltimore*

Low-income residents in Baltimore are more likely to live in houses predating the 1978 Maryland Reduction of Lead Risk in Housing Law.<sup>22</sup> Therefore, these residents have historically had heightened risk of lead paint exposure. Studies also demonstrated that housing communities that were majority African American had a significant risk of lead exposure.<sup>23</sup> Collectively for Baltimore, soil lead levels exceed the national standard of 400 ppm, largely attributed to high vehicular traffic levels in the inner city, which is consistent with other urban areas.<sup>23,24</sup> Lead-contaminated soils in Baltimore are transported by stormwater runoff and cast into nearby water bodies, many of which feed water treatment facilities,

affecting the city's drinking water.<sup>25,26</sup> Lead exposure has a number of detrimental health effects such as abdominal pain, constipation, headache, fatigue, anemia, brain and kidney damage and, in severe cases, death.<sup>27,28,29,30,31,32</sup> Lead exposure has a larger impact on children because they face health issues at lower toxicity levels owing to their developmental stage.<sup>33</sup> More specifically, neurocognitive studies found that blood lead levels in children were inversely related to total IQ level and cognitive function, even at under 30 µg/dL.<sup>34,35</sup>

#### *Air pollution*

Poor air quality in Baltimore can be attributed to several point, mobile, and line sources, many of which have been associated with poor health outcomes in the city. The Environmental Integrity Project (EIP) found that heavy traffic congestion was a primary source of mobile pollution.<sup>36</sup> Through a spatial analysis depicted in Figures 1 and 2, the investigators found a significant overlap between Baltimore neighborhoods with high traffic congestion and high asthma hospitalization rates, as

<sup>17</sup>Isabel Shargo, Jonathan Hall, Ashley Deng, Niya Khanjar, Camryn Edwards, Isabelle Berman, Joseph Galaraga, and Sacoby Wilson. "Proximity of Urban Farms to Contaminated Sites in Baltimore, Maryland." *Landscape Journal* 40, no. 1 (2021): 17–33.

<sup>18</sup>Shannon L. LaDeau, Paul T. Leisnham, Dawn Biehler, and Danielle Bodner. "Higher Mosquito Production in Low-Income Neighborhoods of Baltimore and Washington, DC: Understanding Ecological Drivers and Mosquito-Borne Disease Risk in Temperate Cities." *International Journal of Environmental Research and Public Health* 10, no. 4 (2013): 1505–1526.

<sup>19</sup>Brian Becker, Paul T. Leisnham, and Shannon L. LaDeau. "A Tale of Two City Blocks: Differences in Immature and Adult Mosquito Abundances Between Socioeconomically Different Urban Blocks in Baltimore (Maryland, USA)." *International Journal of Environmental Research and Public Health* 11, no. 3 (2014): 3256–3270.

<sup>20</sup>Eliza Little, Dawn Biehler, Paul T. Leisnham, Rebecca C. Jordan, Sacoby M. Wilson, and Shannon L. LaDeau. "Socio-Ecological Mechanisms Supporting High Densities of *Aedes Albopictus* (Diptera: Culicidae) in Baltimore, MD." *Journal of Medical Entomology* 54, no. 5 (2017): 1183–1192.

<sup>21</sup>Paul T. Leisnham, Shannon L. LaDeau, Megan EM Saunders, and Oswaldo C. Villena. "Condition-Specific Competitive Effects of the Invasive Mosquito *Aedes Albopictus* on the Resident *Culex Pipiens* Among Different Urban Container Habitats May Explain Their Coexistence in the Field." *Insects* 12, no. 11 (2021): 993.

<sup>22</sup>CEEJH. "Redlining, Housing Discrimination, and Environmental Health Disparities in Baltimore, Maryland." ArcGIS StoryMaps, August 20, 2021. <<https://storymaps.arcgis.com/stories/d1c973fb41494614ba0d0c0bcf022cac>>.

<sup>23</sup>Kirsten Schwarz, Richard V. Pouyat, and Ian Yesilonis. "Legacies of Lead In Charm City's Soil: Lessons from the Baltimore Ecosystem Study." *International Journal of Environmental Research and Public Health* 13, no. 2 (2016): 209.

<sup>24</sup>Richard V. Pouyat, Katalin Szlavecz, Ian D. Yesilonis, Christina P. Wong, Laura Murawski, Peter Marra, Ryan E. Casey, and Steven Lev. "Multi-scale Assessment of Metal Contamination in Residential Soil and Soil Fauna: A Case Study in the Baltimore–Washington Metropolitan Region, USA." *Landscape and Urban Planning* 142 (2015): 7–17.

<sup>25</sup>Hyun-Min Hwang, Matthew J. Fiala, Dongjoo Park, and Terry L. Wade. "Review of Pollutants in Urban Road Dust and Stormwater Runoff: Part 1. Heavy Metals Released from Vehicles." *International Journal of Urban Sciences* 20, no. 3 (2016): 334–360.

<sup>26</sup>Roger D Masters, and Myron J. Coplan. "Water Treatment with Silicofluorides and Lead Toxicity." *International Journal of Environmental Studies* 56, no. 4 (1999): 435–449.

<sup>27</sup>CDC. (2018, June 18). Lead: Health Problems Caused by Lead. Centers for Disease Control and Prevention. Retrieved November 15, 2021, from <<https://www.cdc.gov/niosh/topics/lead/health.html>>.

<sup>28</sup>Rodolfo Fonte, Antonio Agosti, Fabrizio Scafa, and Stefano M. Candura. "Anaemia and Abdominal Pain Due to Occupational Lead Poisoning." *Haematologica* 92, no. 2 (2007): e13–e14.

<sup>29</sup>Shiva Mongolu, and Patrick Sharp. "Acute abdominal Pain and Constipation Due To Lead Poisoning." *Acute Med* 12, no. 4 (2013): 224–6.

<sup>30</sup>Kevin C. Staudinger, and Victor S. Roth. "Occupational Lead Poisoning." *American Family Physician* 57, no. 4 (1998): 719.

<sup>31</sup>Jill A. McDonald, and Nancy Upp Potter. "Lead's Legacy? Early and Late Mortality of 454 Lead-Poisoned Children." *Archives of Environmental Health: An International Journal* 51, no. 2 (1996): 116–121.

<sup>32</sup>Anthony J. McMichael, and H. M. Johnson. "Long-term Mortality Profile of Heavily-Exposed Lead Smelter Workers." *Journal of Occupational Medicine* (1982): 375–378.

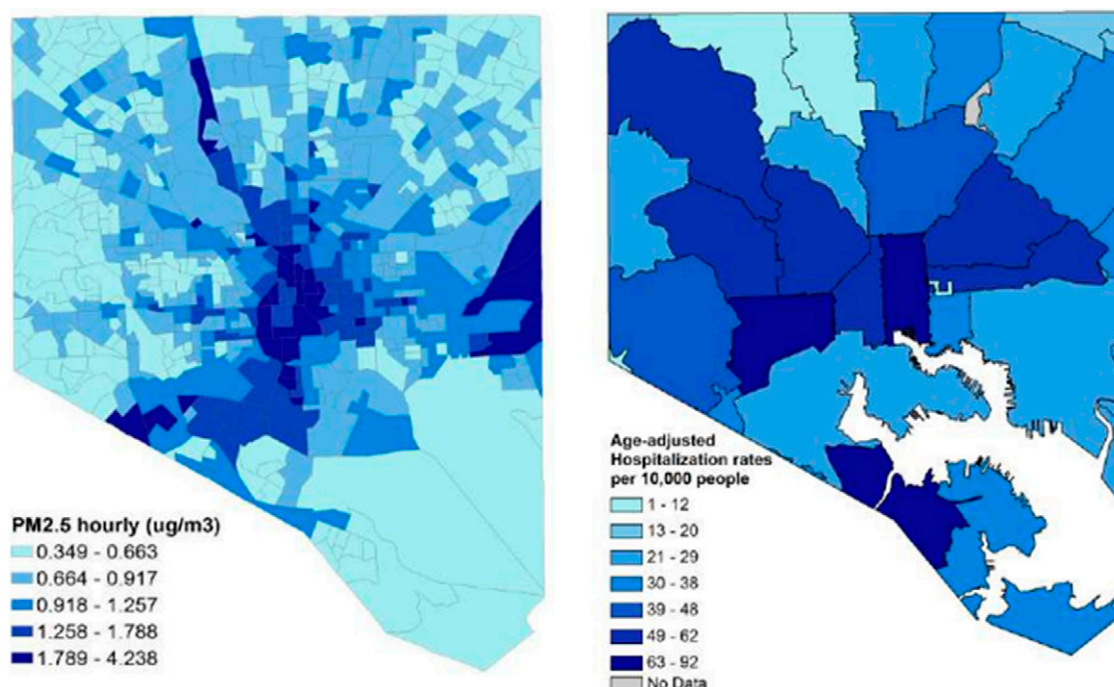
<sup>33</sup>Alan R. Abelsohn, and Margaret Sanborn. "Lead and Children: Clinical Management for Family Physicians." *Canadian Family Physician* 56, no. 6 (2010): 531–535.

<sup>34</sup>Roberto G. Lucchini, Stefano Guazzetti, Stefano Renzetti, Michele Conversano, Giuseppa Cagna, Chiara Fedrighi, Augusto Giorgino et al. "Neurocognitive Impact of Metal Exposure and Social Stressors Among Schoolchildren In Taranto, Italy." *Environmental Health* 18, no. 1 (2019): 1–12.

<sup>35</sup>Kaitlin Vollet Martin, Heidi Sucharew, Kim N. Dietrich, Patrick J. Parsons, Christopher D. Palmer, Robert Wright, Chitra Amarasiriwardena, Donald R. Smith, and Erin N. Haynes. "Co-exposure to Manganese and Lead and Pediatric Neurocognition in East Liverpool, Ohio." *Environmental Research* 202 (2021): 111644.

<sup>36</sup>PROJECT. (2017, December). Asthma and Air Pollution in Baltimore City. Environmental Integrity Project. Retrieved November 14, 2021 <<https://www.environmentalintegrity.org/wp-content/uploads/2017/12/Baltimore-Asthma.pdf>>.





**FIG. 1.** Comparison of hourly PM<sub>2.5</sub> concentrations from traffic-related air pollution in the peak afternoon, Summer 2011 (left) to 2011 Asthma Hospitalization Rates (right).

well Black population.<sup>36</sup> According to the Baltimore County Government, over 32% of daily travel in the city occurs in congested conditions, resulting in 36 hours and \$900 in fuel lost per person per year.<sup>37</sup> Figure 3 presents the breakdown of community statistical areas (CSAs) in Baltimore. Previous research found that Curtis Bay locations had elevated PM<sub>2.5</sub> levels, when compared with Maryland Department of the Environment (MDE) monitoring locations. Compared to suburban areas, there are higher concentrations of PCBs, Ag, Hg, and Zn in downtown Baltimore, which can be ascribed to emissions from a nearby medical incinerator.<sup>38,39</sup>

#### *Health concerns in Baltimore city, Maryland*

The differential burden of environmental hazards and differential exposure to pollution may contribute to disparities in health outcomes observed in Baltimore. Overall, the city has an age-adjusted mortality rate (40%)

higher than the rest of Maryland.<sup>40</sup> In 2010, the EIP found that Baltimore City's rate of asthma-related hospitalizations (40.22 per 10,000 residents) was almost three times higher than the US average (14.1 per 10,000 residents) and about two times higher than the state of Maryland (18.14 per 10,000 residents).<sup>36</sup> The asthma disparity follows sociodemographic lines in regard to hospitalization and emergency room visits in areas of high poverty.<sup>36</sup> Various stakeholders publicly report other health indicator data for Baltimore. A prime example is the Baltimore Neighborhood Indicator Alliance (BNIA), which aggregates information from sources such as the Baltimore City Health Department (BCHD) and Johns Hopkins University. Overall, these groups are crucial for maintaining and utilizing important actionable health indicator data for Baltimore City, Maryland.

The BNIA contains the following health indicators: life expectancy, low-birth weight babies, and all-cause mortality. As defined and sourced by the BCHD, life expectancy refers to the average number of years a newborn can expect to live, assuming he or she experiences the currently prevailing rates of death through their life-span. It is important to note that disparities in life expectancy may exist within populations, especially when subpopulations differ along socioeconomic lines. These

<sup>37</sup>Baltimore County Government. "Baltimore County Md. Planning - Why Walking and Bicycling?" Baltimore County Government, July 23, 2018. <<https://www.baltimorecountymd.gov/departments/publicworks/traffic/pedestrianbicycle/why.html>>.

<sup>38</sup>Qin-Tao Liu, Miriam L. Diamond, Sarah E. Gingrich, John M. Ondov, Polina Maciejczyk, and Gary A. Stern. "Accumulation of Metals, Trace Elements and Semi-Volatile Organic Compounds on Exterior Window Surfaces in Baltimore." *Environmental Pollution* 122, no. 1 (2003): 51-61.

<sup>39</sup>John H. Offenberger, and Joel E. Baker. "Influence of Baltimore's Urban Atmosphere on Organic Contaminants Over the Northern Chesapeake Bay." *Journal of the Air & Waste Management Association* 49, no. 8 (1999): 959-965.

<sup>40</sup>Baltimore City Health Department. 2017 Neighborhood Health Profiles. <<https://health.baltimorecity.gov/stats-and-data>>. Baltimore, MD: Baltimore City Health Department; Maryland Department of Health. Maryland Vital Statistics Annual Report 2016, Table 50, Age Adjusted Death Rates for Selected Causes by Political Subdivision, 2014-2016. Baltimore, MD: Maryland Department of Health.

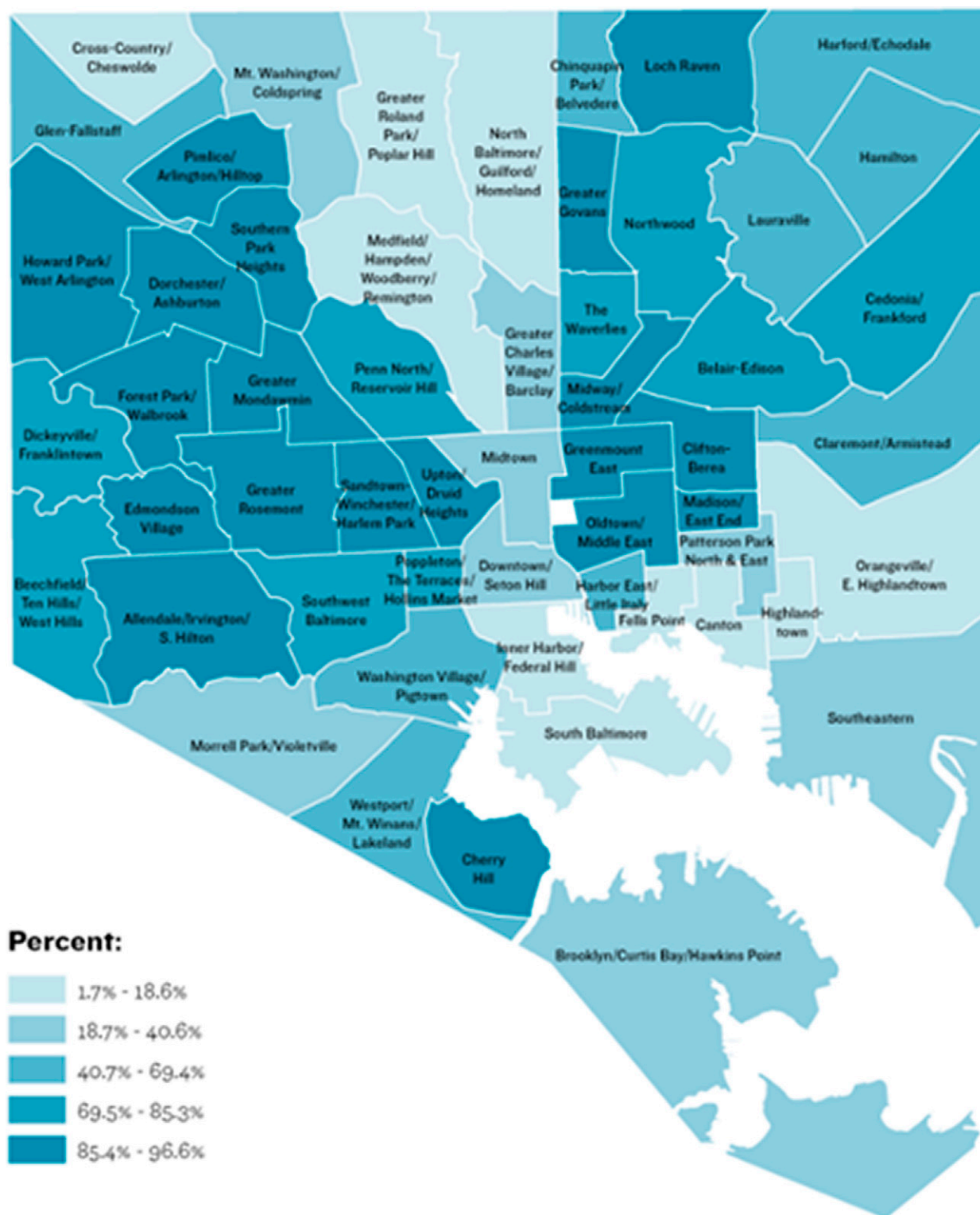
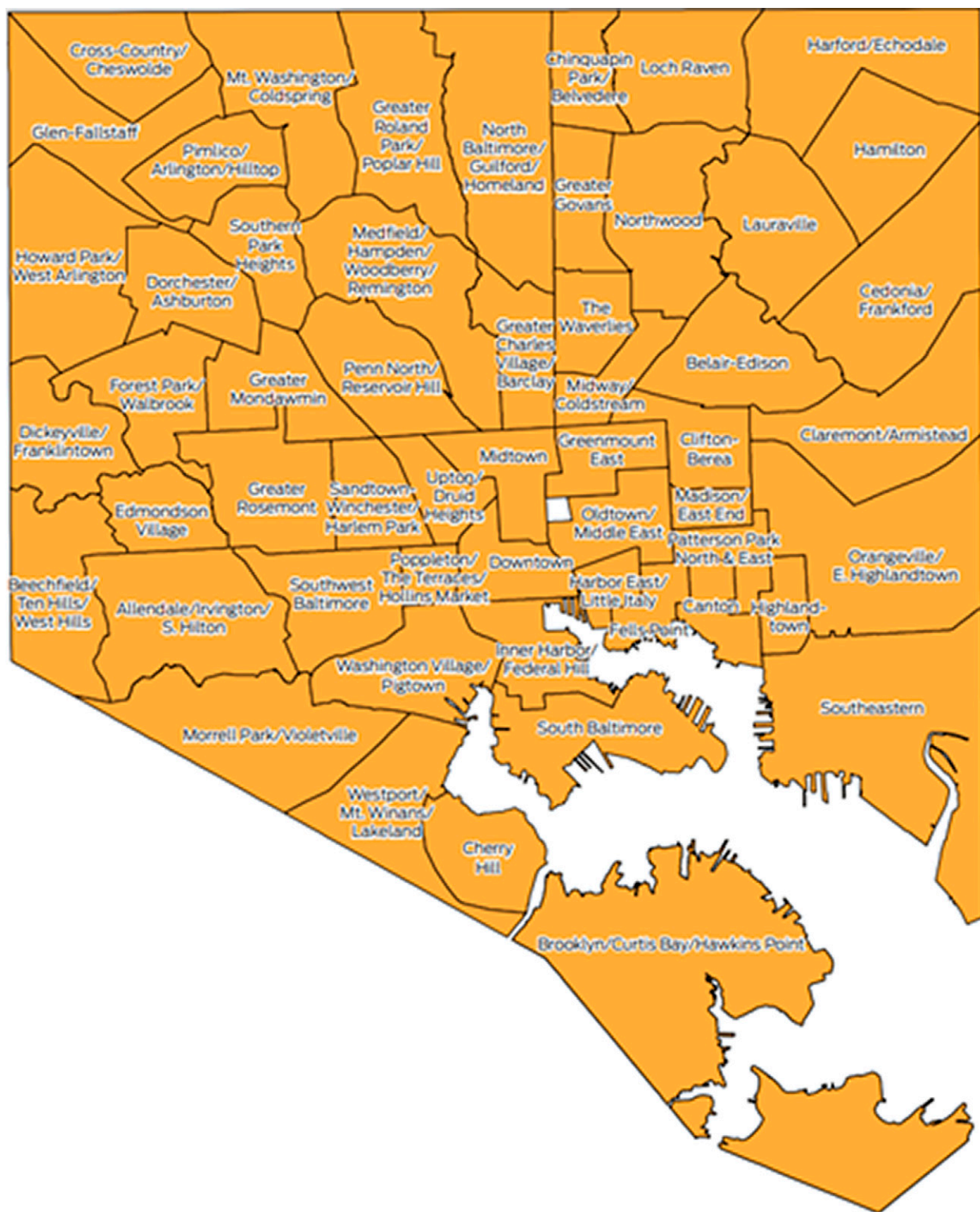


FIG. 2. Percent of residents Black/African American (2012–2016).



**FIG. 3.** Baltimore City community statistical areas (CSAs).



disparities have been further elucidated nationally by the current COVID-19 pandemic.<sup>41,42,43</sup> For example, in 2016, the average life expectancy in Baltimore City was nearly 6 years below the state and national average, while intracity differences were even more disparate.<sup>44</sup> Adequate birth weight corresponded with the percentage of children born at least 5½ pounds. Like life expectancy, this health indicator also follows racial and economic lines.<sup>45,46</sup> 2017 data published by the BNIA reveals that census tracts with >85% African Americans populations tended to have the highest percentage of low-birth weight babies, a known contributor to infant mortality.<sup>47</sup> In 2018, the BCHD reported that the infant mortality rate in Baltimore was 9.1 out of 1000 births, 50.8% higher than the Maryland state average.<sup>48</sup> All-cause mortality refers to the deaths over time within a population.<sup>49</sup> Research has shown mortality rates are disparate across sociodemographic lines within a given population.<sup>50,51</sup> Specifically in Baltimore, there was a significantly higher estimated diabetes mortality rate for

Blacks than Whites, between 2005 and 2007.<sup>52</sup> Because of life expectancy, low-birth weight, and all-cause mortality disparities in Baltimore, there exists a critical need to use the existing BNIA health data to assess the power of existing EJ tools in addressing contributing factors toward these health gaps.

### *The Maryland Environmental Justice Screening Tool*

The use of Geographic Information Systems (GIS) is an innovative method of visualizing both pathogenic (“bad”) and salutogenic (“good”) features of one’s environment in a user-friendly and interactive manner.<sup>53,54,55</sup> However, these tools often operate in silos, presenting a need to consolidate demographic and environmental health data from a multitude of publicly available sources into maps and reports.<sup>56</sup> EJSMT tools have been developed to fill this gap and can be utilized to investigate areas of disparity and need and provide decision-support for corrective action.<sup>57,58</sup> Maryland Environmental Justice Screen (MD EJSCREEN) was built upon the framework of CalEnviroScreen and US EPA EJSCREEN using feedback gathered from stakeholders and community members in Prince George’s County, Maryland.<sup>59</sup> CalEnviroScreen produces a score between 0 and 100, based on the output of 12 measures of environmental exposure, 5 of socioeconomic vulnerability, and 3 of health outcomes.<sup>60</sup> Similar to CalEnviroScreen, EPA EJSCREEN

<sup>41</sup>Theresa Andrasfay, and Noreen Goldman. “Reductions in 2020 US life expectancy due to COVID-19 and the Disproportionate Impact on the Black and Latino Populations.” *Proceedings of the National Academy of Sciences* 118, no. 5 (2021).

<sup>42</sup>Elizabeth Wrigley-Field. “US Racial Inequality May be as Deadly as COVID-19.” *Proceedings of the National Academy of Sciences* 117, no. 36 (2020): 21854–21856.

<sup>43</sup>Meredith S. Shiels, Anika T. Haque, Emily A. Haozous, Paul S. Albert, Jonas S. Almeida, Montserrat García-Closas, Anna M. Nápoles, Eliseo J. Pérez-Stable, Neal D. Freedman, and Amy Berrington de González. “Racial and ethnic disparities in excess deaths during the COVID-19 pandemic, March to December 2020.” *Annals of Internal Medicine* 174, no. 12 (2021): 1693–1699.

<sup>44</sup>Aruna Chandran, Churong Xu, Jonathan Gross, Kathryn M. Leifheit, Darcy Phelan-Emrick, Stephane Helleringer, and Keri N. Althoff. “A Web-Based Tool for Quantification of Potential Gains in Life Expectancy by Preventing Cause-Specific Mortality.” *Frontiers in Public Health* 9 (2021): 861.

<sup>45</sup>Anura WG Ratnasiri, Steven S. Parry, Vivi N. Arief, Ian H. DeLacy, Laura A. Halliday, Ralph J. DiLibero, and Kaye E. Basford. “Recent Trends, Risk Factors, and Disparities in Low Birth Weight in California, 2005–2014: A Retrospective Study.” *Maternal Health, Neonatology and Perinatology* 4, no. 1 (2018): 1–13.

<sup>46</sup>Janardhan Mydam, Richard J. David, Kristin M. Rankin, and James W. Collins. “Low Birth Weight Among Infants Born to Black Latina Women in the United States.” *Maternal and Child Health Journal* 23, no. 4 (2019): 538–546.

<sup>47</sup>Baltimore Neighborhood Indicators Alliance. “Vital Signs 17 Census Demographics Maps.” *Baltimore Neighborhood Indicators Alliance*, 2017.

<sup>48</sup>“B’more for Healthy Babies. “Fetal-Infant Mortality Review in Baltimore City.” (Baltimore, MD: Bureau of Maternal and Child Health Baltimore Health Department, 2016).

<sup>49</sup>CDC. “Mortality Rate.” The Centers for Disease Control and Prevention, May 18, 2012. <<https://www.cdc.gov/csels/dsepd/ss1978/lesson3/section3.html>>.

<sup>50</sup>Rebecca N. Hutchinson, Mary A. Putt, Lorraine T. Dean, Judith A. Long, Chantal A. Montagnet, and Katrina Armstrong. “Neighborhood Racial Composition, Social Capital and Black All-Cause Mortality in Philadelphia.” *Social Science & Medicine* 68, no. 10 (2009): 1859–1865.

<sup>51</sup>May. A. Beydoun, Hind A. Beydoun, Nicolle Mode, Gregory. A. Dore, Jose. A. Canas, Sherif. M. Eid, and Alan. B. Zonderman. “Racial Disparities in Adult All-cause and Cause-Specific Mortality Among Us Adults: Mediating and Moderating Factors.” *BMC Public Health* 16, no. 1 (2016): 1–13.

<sup>52</sup>Summer Rosenstock, Steve Whitman, Joseph F. West, and Michael Balkin. “Racial Disparities in Diabetes Mortality in the 50 Most Populous US Cities.” *Journal of Urban Health* 91, no. 5 (2014): 873–885.

<sup>53</sup>Kristen Burwell-Naney, Sacoby M. Wilson, Xin He, Amir Sapkota, and Robin Puett. “Development of a Cumulative Stressors and Resiliency Index to Examine Environmental Health Risk: A South Carolina Assessment.” *Environmental Justice* 11, no. 4 (2018): 165–175.

<sup>54</sup>Aubree Driver, Crystal Mehdizadeh, Samuel Bara-Garcia, Coline Bodenreider, Jessica Lewis, and Sacoby Wilson. “Utilization of the Maryland environmental justice screening tool: A Bladensburg, Maryland case study.” *International Journal of Environmental Research and Public Health* 16, no. 3 (2019): 348.

<sup>55</sup>Sacoby M. Wilson “An Ecologic Framework to Study and Address Environmental Justice and Community Health Issues.” *Environmental Justice* 2, no. 1 (2009): 15–24.

<sup>56</sup>Gina Cavan, Tom Butlin, Susannah Gill, Richard Kingston, and Sarah Lindley. “Web-GIS Tools for Climate Change Adaptation Planning in Cities.” In *Handbook of Climate Change Adaptation*. (Springer Verlag, Berlin Heidelberg, Germany, 2014).

<sup>57</sup>Charles Lee. “A Game Changer in the Making? Lessons from States Advancing Environmental Justice Through Mapping and Cumulative Impact Strategies.” *Envtl. L. Rep.* 50 (2020): 10203.

<sup>58</sup>Vivek Ravichandran, Rose Albert, Max Teirstein, Anushi Garg, Justice Nagovich, Hamani Wilson, and Sacoby Wilson. Gaps in Environmental Justice Screening and Mapping Tools and Potential New Indicators. National Wildlife Foundation; 2021. <<http://nwf.org/EJSMTtools>>.

<sup>59</sup>Samuel Bara, Aubree Driver, Wengiel Gugssa, Maddie Hagerty, Haley Mullen, Vivek Ravichandran, Vanessa Tellez, and Root Woldu. “A Review of Stakeholder Feedback and Indicator Analysis for the Maryland Environmental Justice Screening Tool.” (2018).

<sup>60</sup>Ben K Greenfield., Jayant Rajan, and Thomas E. McKone. “A Multivariate Analysis of CalEnviroScreen: Comparing Environmental and Socioeconomic Stressors Versus Chronic Disease.” *Environmental Health* 16, no. 1 (2017): 1–16.

produces a single EJ Index between 0 and 100, based on a formula that combines each of its 12 environmental indicators with a demographic indicator respective to the national average and population count for the block group.<sup>61</sup> It considers how much the local demographics are above the national average. Our MD EJSCREEN tool currently consists of four domains—exposure, environmental effects, sensitive populations, and socioeconomic factors. The average scores of the exposure and environmental effects categories are then averaged together and the result is multiplied by the average of the sensitive populations and SES categories to get the total EJSCORE at the census tract level. The full breakdown of specific measures is shown in Table 1. For this study, we aim to determine how well the overall EJSCORE and select MD EJSCREEN indicators, correlate with life expectancy, adequate birth weight, and all-cause mortality in Baltimore, Maryland. The advantage of analyzing the overall MD EJSCORE is the ability for us to deploy our weighted scoring to contextualize both pollution burden and population characteristics, and compare our scoring mechanism to highly regarded mapping tools like CalEnviroScreen and EPA EJSCREEN.

## METHODS

### Data collection

For our analysis, we pulled two subsets of data. MD EJSCREEN data are publicly available online. The data for the indicators are represented as normalized percentile values to allow for meaningful comparisons across tracts. Using the MD EJSCREEN score is preferred over measuring race and environmental impacts separately because it provides a more comprehensive and nuanced picture of environmental injustice. By using the MD EJSCREEN score, researchers and policymakers can identify areas that are not only disproportionately affected by environmental hazards but also have high levels of social vulnerability. This information can help prioritize resources and interventions to address environmental injustice in a more targeted and effective way. Focusing only on race could lead to neglecting other critical factors that contribute to environmental injustice, such as income and education level. Conversely, focusing only on environmental impact could overlook the impact on marginalized communities and their social vulnerability. Our approach is supported by evolving scholarship that indicates an intersectional approach is best for understanding the EJ outcomes of vulnerable urban communities. Intersectionality treats variables, like race and class, as reciprocal, i.e., overlapping and interactive, rather than mutually exclusive characteristics.<sup>62</sup>

BNIA health outcome data were available at the geo-spatial resolution of Community Statistical Areas (CSAs). The City Planning Department, in consultation with local residents, created CSAs to model neighborhoods at the census tract level, since neighborhoods in Baltimore do not typically align with census tract boundaries. There are 55 CSAs in total, defined as condensed clusters of the  $n = 270$  total neighborhoods, organized around Baltimore census tract boundaries. Each CSA consists of 1–8 tracts, with populations between 5000 and 20,000 residents. A total of 194 tracts are included in this dataset. MD EJSCREEN data, modeled at the census tract level, were clipped in GIS to include census tracts within the boundaries of the City of Baltimore, and then were spatially joined to a CSA boundary file for a total of  $n = 55$  CSAs. Within our dataset, these were labeled by corresponding community and neighborhood (e.g., Westport, Belair-Edison). MD EJSCREEN data at the census tract level was aggregated to the CSA level. 2017 BNIA data for life expectancy, birthweight, and all-cause mortality were then joined to the CSA-level MD EJSCREEN data to produce a final dataset for statistical analysis. Table 1 provides a detailed breakdown of the MD EJSCREEN indicators and BNIA health outcome descriptions.

### Statistical analysis

A combination of Excel, Stata version 15.1, and Statistical Analysis Software (SAS) version 9.4 was deployed to perform descriptive and inferential analysis (SAS Institute Inc., Cary, NC).<sup>63,64</sup> Histograms were created to display descriptive statistics for the overall EJSCORE by census tract. The histograms were presented to demonstrate the range of EJSCOREs included in the sample. Pearson correlation coefficients ( $r$ ) were calculated to illustrate the relationships between MD EJSCREEN indicators, life expectancy, low birth weight, and all-cause mortality. The correlations were used as the basis for further investigation with multivariate regression analysis. The standard  $p$  value of 0.05 was used as our significance cutoff.

Simple linear regression (SLR) was performed to determine the association between each indicator independently, with the health outcomes (life expectancy, birth weight, and all-cause mortality) obtained from the BNIA dataset. A coanalysis explored the association between EJSCORE and select independent variables in census tracts: the GINI Index, lead exposure, stormwater, and air pollution-independent variables (PM2.5, traffic proximity, diesel PM).

Five multivariable linear regression (MLR) models were run to investigate the effect of water failure, lead paint, GINI index, and different air quality variables on the EJSCORE. These were run in a stepwise manner so

<sup>61</sup>US Environmental Protection Agency (US EPA). (2021). Environmental Justice Screening Tool (EPA EJSCREEN). <<https://ejscreen.epa.gov/mapper/>>

<sup>62</sup>Jayajit Chakraborty. "Unequal Proximity to Environmental Pollution: An Intersectional Analysis of People with Disabilities in Harris County, Texas." *The Professional Geographer* 72, no. 4 (2020): 521–34. <<https://doi.org/10.1080/00330124.2020.1787181>>.

<sup>63</sup>Curtis Frye. 2007. Microsoft Office Excel 2007 step by step. Redmond, WA: Microsoft Press.

<sup>64</sup>SAS Institute Inc 2013. SAS/ACCESS® 9.4 Interface to ADABAS: Reference. Cary, NC: SAS Institute Inc.



TABLE 1. MD EJSCREEN INDICATORS AND BNIA HEALTH OUTCOME DESCRIPTIONS

<i>Indicator</i>	<i>Description</i>
Percent Low-Income	Percentage of individuals whose household income in the past 12 months is less than two times below the federal poverty level
Percent Non-White	Percentage of individuals who define themselves as any race/ethnicity besides non-Hispanic White
Less than High School Education	Percentage of individuals of age 25 and older who lack a high school diploma
Linguistic Isolation	Percentage of households in which no one among 14 years old and older speaks English “very well,” or households which speak only English
Over 64	Percentage of people over the age of 64
PM <sub>2.5</sub>	Levels of particulate matter with a diameter of 2.5 $\mu\text{m}$ or smaller in air. Reported as micrograms per cubic meter
Ozone	Summer seasonal average of the maximum daily 8-h concentration of ozone in air in parts per billion
Diesel PM	Levels of diesel particulate matter in the air. Reported as micrograms per cubic meter
Traffic Proximity and Volume	Count of vehicles (average annual daily traffic) at major roads within 500 m or close to 500 m, divided by distance in meters
Proximity to Risk Management Plan Sites	Count of RMP (potential chemical accident management plans) facilities within 5 km or close to 5 km, divided by distance in kilometers
Lead Paint Indicator	Percent of houses built before 1960, which likely contain lead paint
Proximity to National Proximity List Sites	Count of NPL/Superfund sites (polluted sites that pose a risk to human health and/or the environment) within 5 km or close to 5 km, divided by distance in kilometers
Proximity to Treatment and Disposal Facilities	Count of TSDF (hazardous waste management facilities) within 5 km or closest to 5 km, divided by distance in kilometers
Proximity to Major Direct Water Discharges	Toxic concentrations in stream segments within 500 m, divided by distance in kilometers. Standards modeled after Risk-Screening Environmental Indicators (RSEI)
Life Expectancy	The average number of years a newborn can expect to live, assuming he or she experiences the currently prevailing rates of death through their lifespan, sourced from the Baltimore City Health Department. 2018 data was used
Percent of Babies Born with Satisfactory Birth Weight	The percentage of children born with a birth weight of at least 5 <sup>1/2</sup> pounds out of all births in the area, sourced from the Maryland Department of Vital Statistics. 2018 data was used
Infant Mortality Rate	The number of infant deaths (babies under one year of age) per 1000 live births within the area in a 5-year period. This is the most stable and commonly measured indicator of mortality in this age group, sourced from the Baltimore City Health Department. 2018 data was used

each indicator was considered for addition to or subtraction from the set of explanatory variables: Model 1 included water failure, lead paint, GINI index, and PM<sub>2.5</sub>. Model 2 included water failure, lead paint, GINI index, PM<sub>2.5</sub>, and traffic proximity. Model 3 included water failure, lead paint, GINI index, traffic proximity, and diesel PM. Model 4 included water failure, lead paint, GINI index, PM<sub>2.5</sub>, and diesel PM. Model 5 included water failure, lead paint, GINI index, and all three air pollution variables (PM<sub>2.5</sub>, traffic proximity, and diesel PM). A combination of particulate matter, traffic proximity, and diesel particulate matter was used in each of the five models to investigate how adjusting for different air quality variables is associated with

EJSCOREs. In addition to the MLR models that investigated the adjustment of various air quality variables in regard to EJSCOREs, best-fit parsimonious models were also ascertained. An adjusted *r*-squared generated the MLR model for each BNIA health outcome.<sup>65,66</sup>

Previous EJ studies have used similar methods to investigate the relationships between environmental hazards and health effects. For example, Morello-Frosch *et al.*

<sup>65</sup>Jeremy Miles. “R-squared, adjusted R-squared.” *Encyclopedia of Statistics in Behavioral Science* (2005).

<sup>66</sup>Hillel Bar-Gera. “The Target Parameter of Adjusted *r*-Squared in Fixed-Design Experiments.” *The American Statistician* 71, no. 2 (2017): 112–119.

used bivariate correlations and multivariate regression analysis to investigate the relationship between lifetime cancer risk and socioeconomic and environmental factors.<sup>67</sup>

## RESULTS

Figure 4 presents a choropleth map of EJSCOREs in Baltimore City using MD EJSCREEN. Compared with the larger Baltimore County and other neighboring regions, we clearly observe the majority of the census tracts in Baltimore City to possess EJSCOREs above 0.80. This is especially true toward the Baltimore Harbor region, and in the southeastern region of the city.

Figure 5 displays a histogram of the distribution of EJSCOREs. The scores ranged from 0.43 to 0.92, with the median score for Baltimore being 0.78, placing the city in the upper quartile when compared to the rest of Maryland. The top 25% of EJSCOREs were labeled as highest priority and were above 0.84. Overall, there is a moderate to strong statistically significant correlation observed between overall EJSCORE and both birth weight ( $r = -0.44$ ;  $p$  value = 0.0009) and life expectancy ( $r = -0.68$ ;  $p$  value < 0.0001). However, little to no association was observed between EJSCORE and all-cause mortality ( $p$  value = 0.80). Along with overall EJSCORE, % people of color ( $r = -0.51$ ;  $p$  value < 0.05), % low income ( $r = -0.51$ ;  $p$  value < 0.05), less than high school education ( $r = -0.42$ ;  $p$  value < 0.05), and demographic index ( $r = -0.50$ ;  $p$  value < 0.05) were moderately and significantly correlated with both birth weight. These indicators were similarly correlated with life expectancy ( $r = -0.49$ ;  $p$  value < 0.05) ( $r = -0.55$ ;  $p$  value < 0.05) ( $r = -0.52$ ;  $p$  value < 0.05) ( $r = -0.59$ ;  $p$  value < 0.05). As was the case with EJSCORE, these indicators were not significantly correlated with all-cause mortality. The environmental indicators (PM2.5, ozone, proximity to hazardous sites, etc.) demonstrated weak associations with birth weight and life expectancy. However, contrary to our observations with the overall EJSCORE and demographic indicators, the environmental indicators had slightly stronger correlations, albeit not significant, with all-cause mortality. All correlations are shown in Table 2.

For the SLR models, only statistically significant models are shown in Table 3. There is overlap among statistically significant indicators (EJSCORE, people of color, low income, less than high school education) for both life expectancy and adequate birth weight. The coefficient ( $\beta$ ) for MD EJSCORE is negative for life expectancy and adequate birth weight, indicating that for every unit increase in Baltimore CSA scores, we observed 90.35 unit decrease in life expectancy and 63.83 unit decrease in adequate birth weight babies. No significance between EJSCORE and all-cause mortality was observed. In the

five MLR models, MD EJSCORE was also consistently statistically significant ( $p < 0.05$ ) for life expectancy and adequate birth weight (Table 4). As was observed in the SLR models, the MD EJSCORE has a negative  $\beta$ , so as the MD EJSCORE increases, life expectancy and adequate birth weight both decrease in Baltimore. In Models 1 and 2, PM2.5 was also statistically significant for those health outcomes. Like MD EJSCORE, PM2.5 also has a negative  $\beta$ , so as the PM2.5 percentile increases, then life expectancy and adequate birth weight decrease. These trends were also observed for adequate birth weight babies. For all-cause mortality, none of the indicators were statistically significant. As for traffic proximity, diesel PM, water failure, lead paint, and GINI index, the point estimates of the sign and magnitude of the  $\beta$  were neither consistent across health outcomes, nor were they significant. Therefore, their values should be taken with caution. See Table 4 for all  $\beta$  and their respective indications for significance.

Table 5 reveals parsimonious models that best predict the three health outcomes. For life expectancy, the following indicators were statistically significant ( $p$  value < 0.05): % over 65, PM2.5, ozone, proximity to Risk Management Plan (RMP), proximity to Treatment, Storage, and Disposal Facility (TSDF), and MD EJSCORE. Of these indicators, MD EJSCORE was most significant ( $p$  value < 0.001). For adequate birth weight, the following indicators were statistically significant: MD EJSCORE, low-income population, PM2.5, ozone, proximity to traffic, and TSDF concentration. Of these indicators, low-income population was the most significant ( $p$  value < 0.001). For all-cause mortality, low-income population and % over 64 were statistically significant. No indicators met the extremely significant threshold of  $p$  value < 0.001. Furthermore, all-cause mortality had the least number of statistically significant indicators, on par with some of the earlier findings.

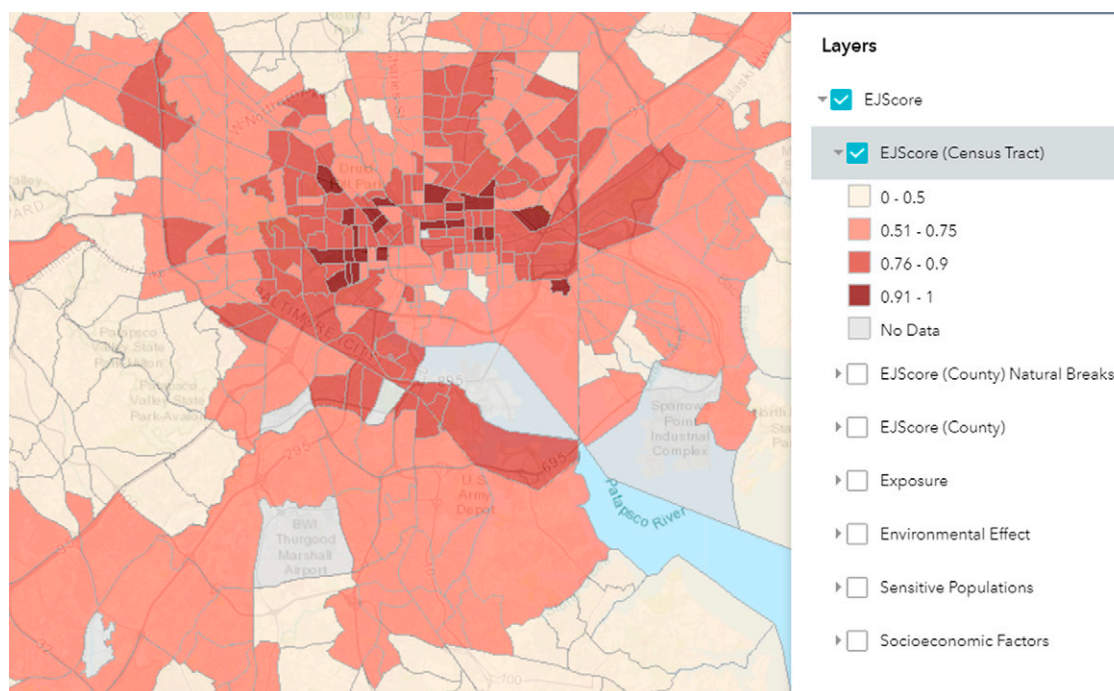
## DISCUSSION

MD EJSCORE was significantly correlated with life expectancy and adequate birth weight, strengthening the validity of the MD EJSCREEN tool as a predictor of adverse health outcomes in the state. PM2.5 was significant in many of the models, confirming its status as one of the most important combustion-related health indicators, as demonstrated in other studies.<sup>68,69</sup> When examining all-cause mortality, none of the MLR models produced statistically significant  $\beta$ s, warranting a deeper look into the

<sup>67</sup>Rachel Morello-Frosch, Manuel Pastor, and James Sadd. "Environmental Justice and Southern California's "Riskscape" the Distribution of Air Toxics Exposures and Health Risks Among Diverse Communities." *Urban Affairs Review* 36, no. 4 (2001): 551–578.

<sup>68</sup>Richard. W. Atkinson, Sujin Kang, H. Ross Anderson, Inga. C. Mills, and Heather. A. Walton. "Epidemiological Time Series Studies of PM2.5 and Daily Mortality and Hospital Admissions: A Systematic Review and Meta-Analysis." *Thorax* 69, no. 7 (2014): 660–665.

<sup>69</sup>Joshua S. Apte, Michael Brauer, Aaron J. Cohen, Majid Ezzati, and C. Arden Pope III. "Ambient PM2.5 Reduces Global And Regional Life Expectancy." *Environmental Science & Technology Letters* 5, no. 9 (2018): 546–551.



**FIG. 4.** Choropleth map of EJ scores in Baltimore using MD EJSCREEN. The unit of analysis is the census tract resolution and EJ scores are presented as normalized percentiles.

metrics used to ascertain the data. This runs counter to other studies that have identified a causal link between constituent EJSCREEN indicators and all-cause mortality.<sup>70,71</sup> The best-fit parsimonious MLR models enable researchers to be economical with the number of indicators present in EJS tools. MD EJSORE, less than high school education, % over 64, PM2.5, ozone, demographic index, RMP, traffic proximity, and proximity to TSDFs were strongly correlated with life expectancy. The relationship between education and life expectancy has been proven in other studies,<sup>72,73</sup> while the existing literature is also dense with moderate-to-strong relationships between the environmental indicators presented above within MD EJSCREEN and

life expectancy.<sup>74,75,76</sup> All of these parameters'  $\beta$  were statistically significant in the MLR model except for population with less than high school education and traffic proximity. Adequate birth weight and all-cause mortality were moderately associated with the MD EJSCREEN indicators, mirroring other studies.<sup>77,78,79,80</sup>

<sup>70</sup>Yan Wang, Itai Kloog, Brent A. Coull, Anna Kosheleva, Antonella Zanobetti, and Joel D. Schwartz. "Estimating Causal Effects of Long-Term PM2.5 Exposure on Mortality in New Jersey." *Environmental Health Perspectives* 124, no. 8 (2016): 1182–1188.

<sup>71</sup>Haidong Wang, Mohsen Naghavi, Christine Allen, Ryan M. Barber, Zulfiqar A. Bhutta, Austin Carter, Daniel C. Casey et al. "Global, Regional, and National Life Expectancy, All-Cause Mortality, and Cause-Specific Mortality for 249 Causes of Death, 1980–2015: A Systematic Analysis for the Global Burden of Disease Study 2015." *The Lancet* 388, no. 10053 (2016): 1459–1544.

<sup>72</sup>Marc A. Garcia, Brian Downer, Chi-Tsun Chiu, Joseph L. Saenz, Kasim Ortiz, and Rebeca Wong. "Educational Benefits and Cognitive Health Life Expectancies: Racial/ethnic, Nativity, and Gender Disparities." *The Gerontologist* 61, no. 3 (2021): 330–340.

<sup>73</sup>Arun S. Hendi. "Trends in Education-Specific Life Expectancy, Data Quality, and Shifting Education Distributions: A Note on Recent Research." *Demography* 54, no. 3 (2017): 1203–1213.

<sup>74</sup>Gerard Hoek, Bert Brunekreef, Sandra Goldbohm, Paul Fischer, and Piet A. van den Brandt. "Association between Mortality and Indicators of Traffic-Related Air Pollution in the Netherlands: A Cohort Study." *The Lancet* 360, no. 9341 (2002): 1203–1209.

<sup>75</sup>Jack M. Guralnik, Kenneth C. Land, Dan Blazer, Gerda G. Fillenbaum, and Laurence G. Branch. "Educational Status and Active Life Expectancy Among Older Blacks and Whites." *New England Journal of Medicine* 329, no. 2 (1993): 110–116.

<sup>76</sup>Amin Kiaghadi, Hanadi S. Rifai, and Clint N. Dawson. "The Presence of Superfund Sites as a Determinant of Life Expectancy in the United States." *Nature Communications* 12, no. 1 (2021): 1–12.

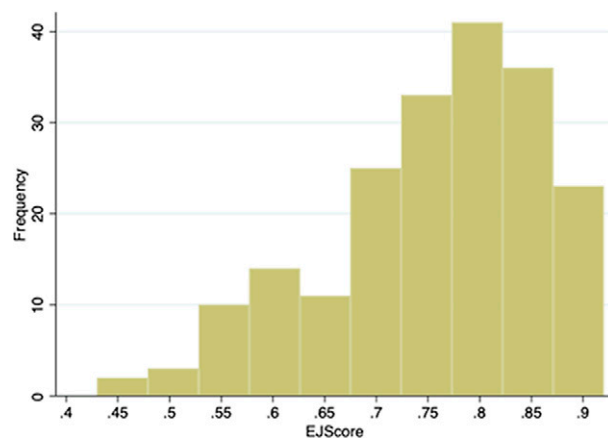
<sup>77</sup>David M. Stieb, Li Chen, Maysoun Eshoul, and Stan Judek. "Ambient Air Pollution, Birth Weight and Preterm Birth: A Systematic Review and Meta-Analysis." *Environmental Research* 117 (2012): 100–111.

<sup>78</sup>Janet Currie, Michael Greenstone, and Enrico Moretti. "Superfund Cleanups and Infant Health." *American Economic Review* 101, no. 3 (2011): 435–41.

<sup>79</sup>Saori Kashima, Hiroo Naruse, Takashi Yorifuji, Shigeru Ohki, Takeshi Murakoshi, Soshi Takao, Toshihide Tsuda, and Hiroyuki Doi. "Residential Proximity to Heavy Traffic and Birth Weight in Shizuoka, Japan." *Environmental Research* 111, no. 3 (2011): 377–387.

<sup>80</sup>Elissa H. Wilker, Elizabeth Mostofsky, Shih-Ho Lue, Diane Gold, Joel Schwartz, Gregory A. Wellenius, and Murray A. Mittleman. "Residential Proximity to High-Traffic Roadways and Poststroke Mortality." *Journal of Stroke and Cerebrovascular Diseases* 22, no. 8 (2013): e366–e372.





**FIG. 5.** Histogram of frequency EJ scores in Baltimore City by census tract.

Overall, this project further cemented the air pollution variables and overall EJScores as suitable indicators.

Other states have used EJS tools to assess relationships between their representative EJScores and health outcomes. The Washington State Environmental Health Disparities Map utilized principal component analysis (PCA) and other statistical methods, and found Washington census tracts that were predominantly communities of color and low-income were more likely to experience higher environmental health disparities.<sup>81</sup> Urban pollution, socioeconomic factors, and traffic-related pollution explained the most variance in the models, with each accounting for 28.71%, 14.43%, and 8.41%, respectively.<sup>81</sup> This coincides with PM<sub>2.5</sub> and traffic proximity being strongly correlated with the BNIA health outcomes in our study models. The Houston–Galveston–Brazoria (HGB) EnviroScreen tool generated an overall ToxPi score that was correlated with concentrations of industrial facilities, low wealth, and communities of color.<sup>82</sup> A multivariate analysis of the CalEnviroScreen tool found that chronic disease burden was more associated with the socioeconomic status indicators within the tool than the environmental ones.<sup>83</sup> This mirrors our Maryland findings where less than high school education and the demographic index indicator were strongly correlated with

**TABLE 2.** PEARSON CORRELATION VALUES OF HEALTH OUTCOMES WITH MD EJScores INDICATORS

	Adequate birth weight	Life expectancy	All- cause mortality
EJ Score	−0.44*	−0.68*	0.03
POC %	−0.51*	−0.49*	0.14
Low Income %	−0.51*	−0.55*	0.07
Less Than HS Edu %	−0.42*	−0.52*	0.11
Linguistically Isolated %	0.12	0.10	−0.16
Over 64%	−0.16	−0.04	0.21
PM <sub>2.5</sub>	−0.10	0.02	−0.22
Ozone	−0.10	0.02	−0.22
Diesel PM	−0.12	−0.06	−0.30
DISPEO	−0.50*	−0.59*	0.20
Pre-1960 Housing	−0.15	−0.05	−0.23
Proximity to RMP	−0.14	−0.15	−0.26
Proximity to TRAF	0.01	−0.06	−0.19
Proximity to NPL	0.07	−0.02	−0.17
Proximity to TSDF	−0.10	−0.12	−0.34
NPL Conc.	−0.04	−0.05	−0.12
TSDF Conc	−0.08	−0.04	−0.15
Prox. To Water Discharge	−0.12	−0.09	−0.13

\*Statistically significant association; *p* value < 0.05.

health outcome, except all-cause mortality. In addition, the CalEnviroScreen Score (CES) was compared with pediatric asthma burden in the state. A one-unit increase in the CES was associated with a 1.6% increase above the mean rate of pediatric asthma hospitalizations. When comparing test–retest reliability of EJS tools, a study found that environmental and demographic indicators in MD EJScores most closely resemble those in EPA EJScores, while the scoring is most similar to CalEnviroScreen.<sup>54</sup> However, other climatic factors such as atmospheric dispersion patterns, wildfires, and confounding factors for respiratory hazard should be considered when validating the study nationwide.<sup>84,85,86</sup>

## LIMITATIONS AND NEXT STEPS

This study was limited by the quality and resolution of the data available in MD EJScores. For example, the data for health indicators included in the EJScores—Asthma Emergency Room Discharges, Myocardial Infarction Discharges,

<sup>81</sup>Esther Min, Deric Gruen, Debolina Banerjee, Tina Echeverria, Lauren Freeland, Michael Schmeltz, Erik Saganić et al. “The Washington State Environmental Health Disparities Map: Development of A Community-Responsive Cumulative Impacts Assessment Tool.” *International Journal of Environmental Research and Public Health* 16, no. 22 (2019): 4470.

<sup>82</sup>Sharmila, P Bhandari, Grace Tee Lewis, Elena Craft, Skylar W. Marvel, David M. Reif, and Weihsueh A. Chiu. “HGBEnviroScreen: Enabling Community Action Through Data Integration in the Houston–Galveston–Brazoria Region.” *International Journal of Environmental Research and Public Health* 17, no. 4 (2020): 1130.

<sup>83</sup>Emanuel Alcala, Paul Brown, John A. Capitan, Mariaelena Gonzalez, and Ricardo Cisneros. “Cumulative Impact of Environmental Pollution and Population Vulnerability on Pediatric Asthma Hospitalizations: A Multilevel Analysis of CalEnviroScreen.” *International Journal of Environmental Research and Public Health* 16, no. 15 (2019): 2683.

<sup>84</sup>Guicai Ning, Steve Hung Lam Yim, Shigong Wang, Bolong Duan, Canqi Nie, Xu Yang, Jinyan Wang, and Kezheng Shang. “Synergistic Effects of Synoptic Weather Patterns and Topography on Air Quality: A Case of the Sichuan Basin of China.” *Climate Dynamics* 53, no. 11 (2019): 6729–6744.

<sup>85</sup>Maíra Feitosa Menezes Macêdo, and André Luis Dantas Ramos. “Vehicle Atmospheric Pollution Evaluation Using AERMOD Model at Avenue in a Brazilian Capital City.” *Air Quality, Atmosphere & Health* 13, no. 3 (2020): 309–320.

<sup>86</sup>Elena Grigorieva, and Artem Lukyanets. “Combined Effect of Hot Weather and Outdoor Air Pollution on Respiratory Health: Literature Review.” *Atmosphere* 12, no. 6 (2021): 790.

TABLE 3. STATISTICALLY SIGNIFICANT SIMPLE LINEAR REGRESSION MODELS

<i>SLR models</i>	<i>Coefficients</i>
Life Expectancy	
MD EJ Score	−90.35**
Less Than High	−22.27**
School Education %	
Low Income %	−11.13**
POC Population %	−5.88*
Adequate Birth	
Weight	
MD EJ Score	−63.83*
POC Population %	−6.73**
Low Income	−11.34**
Population %	
Less Than High	−19.70*
School Education %	
Demographic Index	−0.01**
All-Cause Mortality	
Diesel PM	−288.56*
Proximity to RMP	−57.94*
Proximity to TSDF	−27.76*

The variables included in this model were those showing a significant correlation.

\**p* value < 0.05; \*\**p* value < 0.001.

and Low Birth Weight—are not available at the census tract level owing to privacy concerns related to the Health Insurance Portability and Accountability Act (HIPAA).<sup>87</sup> Thus, the data had to be spatially aggregated from the county level and mathematically modeled to incorporate the census tract level, creating an additional level of uncertainty in the precision of the results across a larger geographical area. In addition, the spatial population apportionment technique used in our analysis, whereby census tract aggregation was conducted using the median of each tract within a CSA, creates a statistical bias where less populous tracts are over-represented and more populous tracts are under-represented. This limitation stems from the use of CSA as a spatial unit of measure, as CSA boundaries do not uniformly align with census tract boundaries. There are also problems associated with using a cumulative score. One is ecological bias, where the statistical methodology inherent to the tool does not reflect spatial patterns. Moreover, pure statistical analyses do not “ground truth” or reflect direct patterns observed in communities, but rather rely on estimates. Therefore, no model is 100% accurate.<sup>88</sup> More robust statistical methods are necessary to select optimal indicators such as the Moran’s *I* test.<sup>89</sup>

<sup>87</sup>Sara E. Grineski, and Yolanda J. McDonald. “Mapping the Uninsured Using Secondary Data: An Environmental Justice Application in Dallas.” *Population and Environment* 32 (2011): 376–387.

<sup>88</sup>George EP Box. “Robustness in the Strategy of Scientific Model Building.” In *Robustness in Statistics* (Academic Press, 1979), pp. 201–236.

<sup>89</sup>Liv Raddatz, and Jeremy Mennis. “Environmental Justice in Hamburg, Germany.” *The Professional Geographer* 65, no. 3 (2013): 495–511.

TABLE 4. COMBINATIONS OF FIVE MULTIPLE LINEAR REGRESSION MODELS PER BNIA HEALTH OUTCOME

	Life expectancy					Adequate birth weight					All-Cause mortality				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
MD EJSCREEN	−103.9*	−114.2*	−108.0*	−106.3*	−113.5*	−63.3*	−75.8*	−66.6*	−69.6*	−76.6*	−623.8	−221.8	−389.3	194.3	98.6
Water Failure	−0.03	−0.06	−0.05	−0.04	−0.06	0.05	0.02	0.03	0.03	0.01	−12.4	−11.3	−10.9	−9.9	−10.1
Lead Paint	5.7	7.3	8.9	5.0	8.0	−10.2	−8.23	−7.4	−11.9	−9.1	273.8	212.6	463.8	504.9	543.9
GINI Index	4.8	3.9	3.9	4.6	4.0	9.5	8.4	8.2	8.9	8.3	351.5	386.4	430.1	431.7	424.1
Air Quality															
PM <sub>2.5</sub>	−0.4*	−0.6*		−0.6	−0.4	−0.5*	−0.7*		−1.0	−0.8	−29.0	−23.1		36.9	39.2
Traffic Proximity		0.001	0.001		0.001		0.001	0.001		0.001		−0.04	−0.0004	−633.7	0.01
Diesel			−5.2*	1.9	−1.4			−5.2*	4.8	1.6			−343.5		−677.3

The independent variables are all reported in percentiles.

Models differ on air quality variables: Model 1 includes PM<sub>2.5</sub>, Model 2 includes PM<sub>2.5</sub> and traffic proximity, Model 3 includes traffic proximity and NATA Diesel PM, Model 4 includes PM<sub>2.5</sub> and diesel PM, Model 5 includes all three air pollution variables.

\**p* < 0.05.

PM, particulate matter.

TABLE 5. BEST FIT PARSIMONIOUS MODELS FOR HEALTH OUTCOMES IN BALTIMORE COUNTY

	Parameter	Coefficients
Life Expectancy (Adjusted <i>r</i> -squared = 0.7078)	Intercept	82.67**
	MD EJ Score	−83.09**
	Less Than High School	−8.88
	Over 64	12.23*
	PM <sub>2.5</sub>	−30.73*
	Ozone	5.83*
	Demographic Indicator	−0.008**
	Proximity to RMP	−0.99*
	Proximity to Traffic	0.0006
	Proximity to TSDF	0.50*
Adequate Birth Weight (Adjusted <i>r</i> -squared = 0.4618)	Intercept	95.43**
	MD EJ Score	−48.78*
	Low-Income	−16.71**
	Less Than High School	9.06
	PM <sub>2.5</sub>	−69.75*
	Ozone	13.35*
	Proximity to Traffic	0.001*
	Proximity to TSDF	0.31
	TSDF Concentration	−1.00*
	Intercept	1890.66**
All-Cause Mortality (Adjusted <i>r</i> -squared = 0.3180)	MD EJ Score	−2862.24
	Low-Income	846.06*
	Over 64	1526.47*
	PM <sub>2.5</sub>	2435.88
	Ozone	−482.19
	Proximity to TSDF	−24.36
	Proximity to Water Discharge Site	−7.13

Lastly, there remains an issue of comparing an index (EJSCORE) to individual composite indicators. Because of this inherent dependency, correlation and regression results carry a degree of bias.<sup>90</sup> Future iterations of this study should assess the associations between the MD EJSCORE and select externally derived indicators that do not contribute directly to its scoring.

Future projects using MD EJSCREEN should also address climate inequities, which are currently largely outside the scope of the tool. While the tool does include the urban heat island effect, MD EJSCREEN should be expanded to include: sea level rise, storm surge inundation, and projected changes in precipitation.<sup>91,92</sup> Other indicators within the climate domain should include: the Climate and Ocean Risk Vulnerability Index (CORVI),<sup>93</sup> the Heat Vulnerability Index,<sup>94</sup> and area in flood zone.<sup>95</sup> Other domains to include

within future iterations of this tool are health disparity measures. These should include: the slope index of inequality, net difference score, relative index of inequality, and index of disparity.<sup>96,97</sup>

## CONCLUSION

This study cements the MD EJSCORE as a key indicator of EJ concern in Baltimore, owing to its constituent environmental and demographic indicators displaying a strong correlation with life expectancy and adequate birth weight. This was present across all statistical tests performed in the

2020. <<https://www.stimson.org/2020/corvi-report-climate-and-ocean-risk-vulnerability-index/>>.

<sup>94</sup>Junzhe Bao, Xudong Li, and Chuanhua Yu. "The Construction and Validation of The Heat Vulnerability Index, A Review." *International Journal of Environmental Research and Public Health* 12, no. 7 (2015): 7220–7234.

<sup>95</sup>Minkyu Park, Youngseok Song, Sangdan Kim, and Moojong Park. "A study on the assessment method for high-risk urban inundation area using flood vulnerability index." *Journal of the Korean Society of Hazard Mitigation* 12, no. 2 (2012): 245–253.

<sup>96</sup>Margarita Moreno-Betancur, Aurélien Latouche, Gwenn Menvielle, Anton E. Kunst, and Grégoire Rey. "Relative Index of Inequality and Slope Index of Inequality: A Structured Regression Framework for Estimation." *Epidemiology* 26, no. 4 (2015): 518–527.

<sup>97</sup>Mona Ray. "Environmental Justice: Segregation, Noise Pollution and Health Disparities near the Hartsfield-Jackson Airport Area in Atlanta." *The Review of Black Political Economy* 50, no. 1 (2023): 18–34.

<sup>90</sup>Kenneth A. Bollen, and Shawn Bauldry. "Three Cs in Measurement Models: Causal Indicators, Composite Indicators, and Covariates." *Psychological Methods* 16, no. 3 (2011): 265.

<sup>91</sup>Douglas Marcy, William Brooks, Kyle Draganov, Brian Hadley, Chris Haynes, Nate Herold, John McCombs et al. "New Mapping Tool and Techniques for Visualizing Sea Level Rise and Coastal Flooding Impacts." In *Solutions to Coastal Disasters 2011*, pp. 474–490. 2011.

<sup>92</sup>MARISA. (n.d.). Projected Intensity-Duration-Frequency (IDF) Curve Data Tool for the Chesapeake Bay Watershed and Virginia. Mid-Atlantic Regional Integrated Sciences and Assessments. Retrieved November 16, 2021. <<http://midatlantic-idf.rcc-acis.org/>>.

<sup>93</sup>Tracy Rouleau, Jack Stuart, and Sally Yozell. "The Climate and Ocean Risk Vulnerability Index ." Stimson Center, June 1,



study. Furthermore, PM<sub>2.5</sub> was a strong indicator of EJSCORE and health outcome status. Therefore, while it is useful to study all-cause mortality to improve population health,<sup>98</sup> the results indicate that more specific measures of health (i.e., life expectancy, children's health outcomes) and environmental hazard exposure would better allow microtargeting of interventions.<sup>99</sup> For example, policy directed at lead paint oversight, safety standards, and other mitigation efforts would help to reduce overall MD EJSCORE and subsequently improve population health for communities facing environmental injustice.

Ongoing Maryland legislative efforts to reduce pollution in Baltimore include the 2022 Baltimore Transit Equity Act, which would require transit equity analyses, cost-benefit analysis, and outreach to affected communities before public hearings on any major service change.<sup>100</sup> Another initiative is Senate Bill 0616, which would remove dirty energy derived from incinerators from Maryland's Renewable Portfolio Standard (RPS) clean energy program.<sup>101</sup> Beyond these programs, Maryland is encouraged to further adopt standards to improve air quality in disadvantaged communities. Bills that allow the state to deny permits causing pollution, encourage the use of electric cars, and promote clean energy have been implemented in other states to reduce air quality disparities, such as New Jersey, Minnesota, and California.<sup>102,103,104,105</sup> More specifically, California's Senate Bill 1000 requires the state to employ cumulative impact analysis to determine whether electric vehicle

charging stations are disproportionately deployed, and use state funds to correct these disparities.<sup>106</sup> These bills can serve as examples of legislative mechanisms that Maryland could replicate to make use of MD EJSCREEN. The tool itself can serve to microtarget communities based on priority scoring. Researchers can then confirm concerns with residents and to formulate solutions utilizing techniques such as the community-based participatory research (CBPR) framework.<sup>107,108,109</sup>

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## AUTHORS' CONTRIBUTIONS

V.R.: methodology, investigation, formal analysis, validation, original draft preparation, writing—review and editing; J.-M.A.: investigation, validation, formal analysis, visualization, writing—review and editing; L.A.: writing—review and editing; J.T.: validation, data curation, and visualization; M.T.: methodology, investigation, formal analysis, and validation; A.S.: writing—reviewing

<sup>98</sup>Sheena E. Martenies, Chad W. Milando, Guy O. Williams, and Stuart A. Batterman. "Disease and Health Inequalities Attributable to Air Pollutant Exposure in Detroit, Michigan." *International Journal of Environmental Research and Public Health* 14, no. 10 (2017): 1243.

<sup>99</sup>Juliana Maantay, Jayajit Chakraborty, and Jean Brender. "Proximity to Environmental Hazards: Environmental Justice and Adverse Health Outcomes." In *Strengthening Environmental Justice Research and Decision Making: A Symposium on the Science of Disproportionate Environmental Health Impacts*, pp. 17–19. 2010.

<sup>100</sup>LegiScan. "Maryland SB23." LegiScan, 2022. <<https://legiscan.com/MD/bill/SB23/2022>>.

<sup>101</sup>Maryland General Assembly. "Legislation—SB0616." Maryland General Assembly, 2022. <<https://mgaleg.maryland.gov/mgaweb/Legislation/Details/sb0616>>.

<sup>102</sup>NJ Assembly and Senate Just Passed National Precedent Setting Environmental justice Bill This afternoon. Insider NJ. (2020, August 27). Retrieved November 16, 2021, <<https://www.insidernj.com/press-release/nj-assembly-senate-just-passed-national-precedent-setting-environmental-justice-bill-afternoon/>>

<sup>103</sup>New Jersey State Legislature. (2020). S232. New Jersey State Legislature. <<https://www.njleg.state.nj.us/bills/BillView.asp?BillNumber=S232>>.

<sup>104</sup>Office of the Revisor of Statutes. (2021). 2021 Minnesota Statutes. Minnesota Legislature. Retrieved November 16, 2021, <<https://www.revisor.mn.gov/statutes/cite/116.07#stat.116.07.4a>>.

<sup>105</sup>California Global Warming Solutions Act of 2006: Greenhouse Gas Reduction Fund, SB535, California State Senate, 2011–2012, (2012). <[https://leginfo.ca.gov/faces/billTextClient.xhtml?bill\\_id=201120120SB535](https://leginfo.ca.gov/faces/billTextClient.xhtml?bill_id=201120120SB535)>

<sup>106</sup>Land Use: General Plans: Safety and Environmental Justice, SB1000, California State Senate, 2015–2016, (2016). <[https://leginfo.ca.gov/faces/billNavClient.xhtml?bill\\_id=201520160SB1000](https://leginfo.ca.gov/faces/billNavClient.xhtml?bill_id=201520160SB1000)>

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#### **CONFLICT OF INTEREST**

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the article; or in the decision to publish the results.

Address correspondence to:

*Vivek Ravichandran  
Maryland Institute for Applied Environmental Health  
School of Public Health  
University of Maryland  
4200 Valley Drive  
College Park, MD 20742  
USA*

*E-mail: vravicha@terpmail.umd.edu*