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Mapping and Measuring Environmental Justice: A Case Study of Bioenergy Development in Michigan, USA

Sarah Mittlefehldt, Erin Bunting, Joseph Welsh, and Emily Huff

ABSTRACT

The Biden Administration's Justice40 Initiative states that 40% of federal investment in clean energy needs to benefit historically disadvantaged communities. This unprecedented policy has contributed to greater interest in how to measure environmental justice (EJ) and account for the disparate impacts that renewable energy development may have on different communities. This research uses spatial data to map and measure EJ in the context of bioenergy development. A geographic information system (GIS) database was developed to compare data from Michigan's MiEJScreen tool to the location of different types of wood energy technologies, including residential wood heating, commercial boilers, pellet manufacturing facilities, and biomass power stations. The results of statistical analyses using ArcGIS Pro found that as MiEJScreen values increased, the use of residential wood heat decreased. A hotspot analysis found that, in general, commercial boilers, pellet plants, and power stations were not clustered in areas with high MiEJScreen scores, although there were important exceptions. For all scales of wood energy technologies, rurality seemed to drive associations. Tools such as MiEJScreen can help to illuminate broader environmental and socioeconomic landscapes in which bioenergy technologies have been developed, but they may miss important nuances, particularly in rural communities. Implementing federal policies that aim at EJ requires accurate ways of mapping and measuring community dynamics and regional differences. This study uses the context of bioenergy development in Michigan to show how different analyses can be used, and some of the strengths and limitations of the existing tools and approaches.

Keywords: environmental justice, bioenergy, spatial analysis, renewable energy metrics

INTRODUCTION

The Biden Administration's Justice40 Initiative states that 40% of federal investment in clean energy development needs to benefit historically disadvantaged communities.[1] This unprecedented national policy directive has contributed to greater interest in how to measure environmental justice (EJ) and account for the disparate impacts that renewable energy development may have on different communities. This research contributes to a growing body of scholarship that examines how renewable energy systems have distributed benefits and burdens, and how different scales and forms of renewable energy technologies are likely to affect—and be affected by—social relations, power structures, and environmental

Sarah Mittlefehldt is at Department of Earth, Environmental & Geographical Sciences, Northern Michigan University, Marquette, Michigan, USA. Erin Bunting is at Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, Michigan, USA. Joseph Welsh is at Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, Michigan, USA. Emily Huff is at Department of Forestry, Michigan State University, East Lansing, Michigan, USA.

[1]White House. Justice 40: A Whole-of-Government Initiative. https://www.whitehouse.gov/environmentaljustice/justice40/ (Last accessed on October 21, 2023).

legacies.[2] Specifically, this article demonstrates different ways of using spatial data to map and measure EJ in the context of bioenergy development, and contributes to existing scholarship on the strengths and limitations of tools such as EJScreen or MiEJScreen.[3]

According to the International Energy Agency, bioenergy comprises 55% of the world's renewable energy supply and is expected to increase.[4] Bioenergy is defined as a renewable form of energy that is produced from organic feedstocks such as agricultural wastes, wood residuals (material leftover after harvesting trees or milling forest products), algae, grasses, or woody crops grown to produce energy, or other nonfossil-based sources. These organic feedstocks, known as biomass, can be converted for use in a wide range of applications, including transportation, heat, electricity, or bioproducts.[5] Despite the growth of bioenergy technologies, there is little research explaining how different types of bioenergy applications have contributed to geographies of inequality.[6] This study focuses on the EJ implications of different wood-burning energy technologies. Similar to all energy sources, wood-fired energy technologies can be beneficial, but can also have unintended consequences. In forested areas, wood can be an affordable way to heat homes and buildings using locally available resources. Boilers at sawmills and forest product manufacturing centers can maximize the efficiency of operations by using wood waste to heat and power facilities. In rural areas with active forest markets, using logging and mill residues for bioenergy can provide jobs and additional economic benefits.[7] Wood energy can also be part of diversified energy portfolios that aim to reduce greenhouse gas (GHG) emissions.[8]

Although burning wood produces several GHGs, including carbon dioxide (CO_2), nitrogen oxides (NO_x), and methane, policymakers have considered wood to be a carbon neutral energy source because carbon dioxide emitted from burning trees can be absorbed by existing intact forests that act as carbon sinks.[9] A comparison of conventional energy sources to the life cycle of different forms of wood energy found that across applications, wood energy avoided 2%–19% of the GHG emissions from comparable sources of energy.[10] Burning wood also produces non-GHG emissions such as coarse and fine particulates (PM_{10} and $PM_{2.5}$), polyacrylic aromatic hydrocarbons such as benzene, and carcinogenic chemicals such as phenols and dioxin.[11] These pollutants can be harmful to human health.

Prior research has revealed complicated racial and economic dynamics surrounding woody biomass development in different regions of the United States. In a broad study of forest-based bioenergy development in the South, Hitchner et al. found that the economic benefits from new large-scale biomass energy plants have not been equally distributed and have been shaped by racial divisions from the past.[12] These findings were supported by another study on biomass energy in the Southeast that found wood pellet production facilities were 50% more likely to be located in EJ-designated communities. That study defined EJ communities to be those where at least 25% of the population is nonwhite and where the poverty level is above the state median.[13]

This research builds upon prior studies by using data available through MiEJScreen to examine the EJ implications of

[2]Benjamin K. Sovacool, Matthew Burke, Lucy Baker, Chaitanya Kumar Kotikalapudi, Holle Wlokas. "New frontiers and conceptual frameworks for energy justice." *Energy Policy* 105 (2017): 677–691; Darren McCauley and Raphael Heffron. "Just transition: Integrating climate, energy and environmental justice." *Energy Policy* 119 (2018): 1–7.

[3]Haley Mullen, Kyle Whyte, Ryan Holifield "Indigenous Peoples and the Justice40 Screening Tool: Lessons from EJScreen." *Environmental Justice* 16 (2023): 360–369.

[4]International Energy Agency, "Tracking Bioenergy." https://www.iea.org/energy-system/renewables/bioenergy# (Last accessed November 2, 2023).

[5]US Department of Energy, Office of Energy Efficiency and Renewable Energy, "Bioenergy Basics," https://www.energy.gov/eere/bioenergy/bioenergy-basics#:~:text=Bioenergy%20is%20one%20of%20many,heat%2C%20electricity%2C%20and%20products (Last accessed February 12, 2024).

[6]Most research on the human dimensions of wood-based bioenergy has focused on attitudes and perceptions, and the willingness of landowners to contribute to biomass supply. For example, see Emily S. Huff, Sarah Mittlefehldt, Erin Bunting, Joseph Welsh. "Attitudes and perceptions of wood energy technologies in Great Lakes region." *Biomass and Bioenergy* 176 (2023): 106897; Omkar Joshi and Sayeed R. Mehmood. "Factors Affecting Nonindustrial Private Forest Landowners' Willingness to Supply Woody Biomass for Bioenergy." *Biomass and Bioenergy* 35 (2011): 186–192; Zach J. Leitch, John Lhotka, George A. Stainback, Jeffery W. Stringer. "Private Landowner Intent to Supply Woody Feedstock for Bioenergy Production." *Biomass and Bioenergy* 56 (2013): 27–136; Dennis R. Becker, Derya Eryilmaz, Jonathan J. Klapperich, Michael A. Kilgore. "Social Availability of Residual Woody Biomass from Nonindustrial Private Woodland Owners in Minnesota and Wisconsin." *Biomass and Bioenergy* 56 (2013): 82–91. Less is known about the environmental justice implications of different types of bioenergy technologies.

[7]Jianbang Gan and C.T. Smith, C.T. "Co-benefits of Utilizing Logging Residues for Bioenergy Production: The Case for East Texas, USA." *Biomass and Bioenergy* 31 (2007): 623–630.

[8]Francisco X. Aguilar. "Wood Energy in the EU and US: Assessment and Outlook to 2030" in *Wood Energy in Developed Economies.* (New York: Routledge, 2014), 306–327.

[9]Roger A. Sedjo, R.A. "Comparative Life Cycle Assessments: Carbon Neutrality and Wood Biomass Energy." Resources for the Future DP 13–11 (2013). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2286237 (Last accessed October 21, 2023); Francisco X. Aguilar, Houston Sudekum, Ronald McGarvey, Benjamin Knapp, Grant Domke, Consuelo Brandeis. "Impacts of the US Southeast Wood Pellet Industry on Local Forest Carbon Stocks." *Nature Scientific Reports* 12 (2022) 19449.

[10]Ann Kristen Petersen Raymer. "A Comparison of Avoided Greenhouse Gas Emissions when Using Different Kinds of Wood Energy." *Biomass and Bioenergy* 30 (2006): 605–617.

[11]Luke P. Naeher, Michael Brauer, Michael Lipsett, Judith T. Zelikoff, Christopher D. Simpson, Jane Q. Koenig, Kirk R. Smith. "Woodsmoke Health Effects: A Review," *Inhalation Toxicology*, 19 (2007): 67–106.

[12]Sarah Hitchner, John Schelhas, J. Peter Brosius. *Forests as Fuel: Energy, Landscape, Climate, and Race in the U.S. South* (Lanham, MD: Lexington Books, 2022).

[13]Stefan Koester and Sam Davis. "Siting of Wood Pellet Production Facilities in Environmental Justice Communities in the Southeastern United States." *Environmental Justice* 11 (2018): 64–70.

different types of wood-based bioenergy in Michigan. Michigan has been an epicenter of EJ research and activism since at least the 1990s and is also one of the largest consumers of wood energy in the United States.[14] As shown in Figure 1, of the total 99.7 trillion BTUs of wood and biomass waste consumed in Michigan in 2021, 44% was used for industrial production, 27% for residential heat, and 23% for producing electrical power (Fig. 1).[15]

This analysis focuses on the spatial distribution of four different types of wood-burning energy technologies across Michigan, including (1) residential-scale thermal applications (e.g., indoor woodstoves, furnaces, fireplaces, pellet stoves, and outdoor wood boilers); (2) community- or commercial-scale boilers used for heating public spaces and private industries; (3) wood pellet manufacturing facilities; and (4) biomass power stations.[16] Each of these wood energy applications produces air pollutants in different levels and each uses different mechanisms to control emissions. For example, the Environmental Protection Agency (EPA) has efficiency standards for residential woodstoves, larger commercial boilers are regulated by the state's Department of Licensing and Regulatory Affairs (LARA), pellet manufacturing facilities and biomass power plants are regulated by both state and federal agencies. To examine the landscapes in which these technologies have been developed, this research uses publicly available data from Michigan's Department of Environment, Great Lakes, and Energy's (EGLE) MiEJScreen Environmental Justice Screening Tool and information from archives to map and measure the EJ implications of different applications. Our thesis is twofold: first, different types and scales of wood-based bioenergy technologies have different implications for EJ, and second, quantitative datasets such as MiEJScreen may be helpful to policymakers but insufficient to understand historical legacies and nuanced community dynamics, particularly in rural areas.

METHODS

GIS database development

To compare community characteristics of places with wood energy technologies, we developed a GIS database that included locations of wood-burning technologies, metrics of EJ, and U.S. Census data. One layer contained information from the U.S. Census, specifically the American Community Survey 5-year estimates (2016–2020), about the percentage of households that use wood as a primary heat source.[17] Another layer contained the location of 118 regulated commercial boilers that use wood-derived fuels to heat larger spaces.[18] These data points were obtained from Michigan's LARA Boiler Division.[19] LARA also provided information for a third layer in the GIS database that showed the location of power plants in Michigan that use wood and cellulosic material to create electricity or a combination of heat and power (CHP). A fourth layer contained information on the location of four pellet manufacturing facilities in Michigan. Those data were obtained from an industry website that listed all pellet manufacturers in the United States.[20]

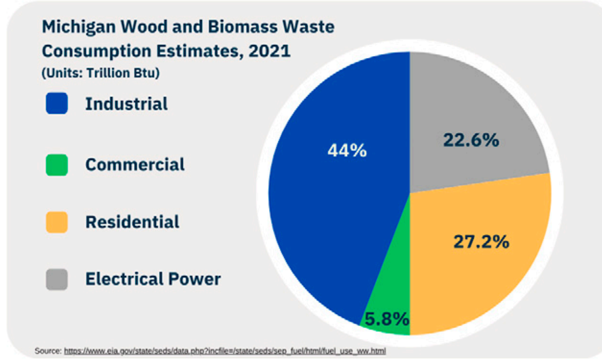

FIG. 1. Shows how the total 99.7 trillion BTUs of wood and biomass waste consumed in Michigan in 2021 break down between different energy uses. Data from the U.S. Energy Information Administration.

To examine EJ characteristics of places with these different types of wood-based bioenergy technologies, we

[14]Bunyan Bryant and Elaine Hockman. *Michigan: A State of Environmental Justice?* (New York: Morgan James Publishing, 2011).

[15]U.S. Energy Information Administration, "Wood and Biomass Waste Consumption Estimates, 2021." https://www.eia.gov/state/seds/data.php?incfile=/state/seds/sep_fuel/html/fuel_use_ww.html (Last accessed November 5, 2023).

[16]Although wood can be transformed into liquid biofuels through thermochemical processes, wood is more commonly turned into energy through direct combustion technologies, which are the focus of this article.

[17]There are many types of residential wood heating technologies including woodstoves and inserts, fireplaces, pellet stoves, indoor wood boilers, forced-air furnaces, and outdoor wood boilers. The American Community Survey administered by the US Census does not ask respondents to specify what type of wood heater residents use, but simply asks if people use wood as a primary fuel source to heat their homes. Because of this limitation, this study does not compare different types of residential heating technologies. US Census Bureau, House Heating Fuel. https://data.census.gov/table/ACSDT5Y2020.B25040?q=Primary%20fuel&g=040XX00US26$1400000&tp=true (Last accessed February 15, 2024).

[18]According to Michigan statute, commercial boilers are those that heat public facilities, non-residential buildings, apartment complexes with six or more units, or group home or foster case-type facilities with six or more clients. Michigan Skilled Trades Regulation Act 407. 2016. Article 9. Boiler Inspectors, Installers, Repairers, and Operations and Stationary Engineers. http://www.legislature.mi.gov/(S(i3gpjdykc1otzwn0ajhi34ji))/documents/mcl/pdf/mcl-407-2016-9.pdf (Last accessed October 21, 2023).

[19]Michigan's Department of Licensing and Regulatory Affairs' (LARA) Boiler Division oversees the operation of different types of boilers and tracks technologies by fuel types among other characteristics. Boilers that use wood or other forms of cellulosic material, including bark chips, wood chips, wood waste, paper waste, or pellets are categorized as "other solid." We obtained data on the location and other characteristics of these wood-fired commercial boilers from LARA, and integrated these data into the project's GIS database.

[20]Biomass Magazine, U.S. Pellet Plants. 2023. https://biomassmagazine.com/plants/listplants/pellet/US/ (Last accessed October 21, 2023).

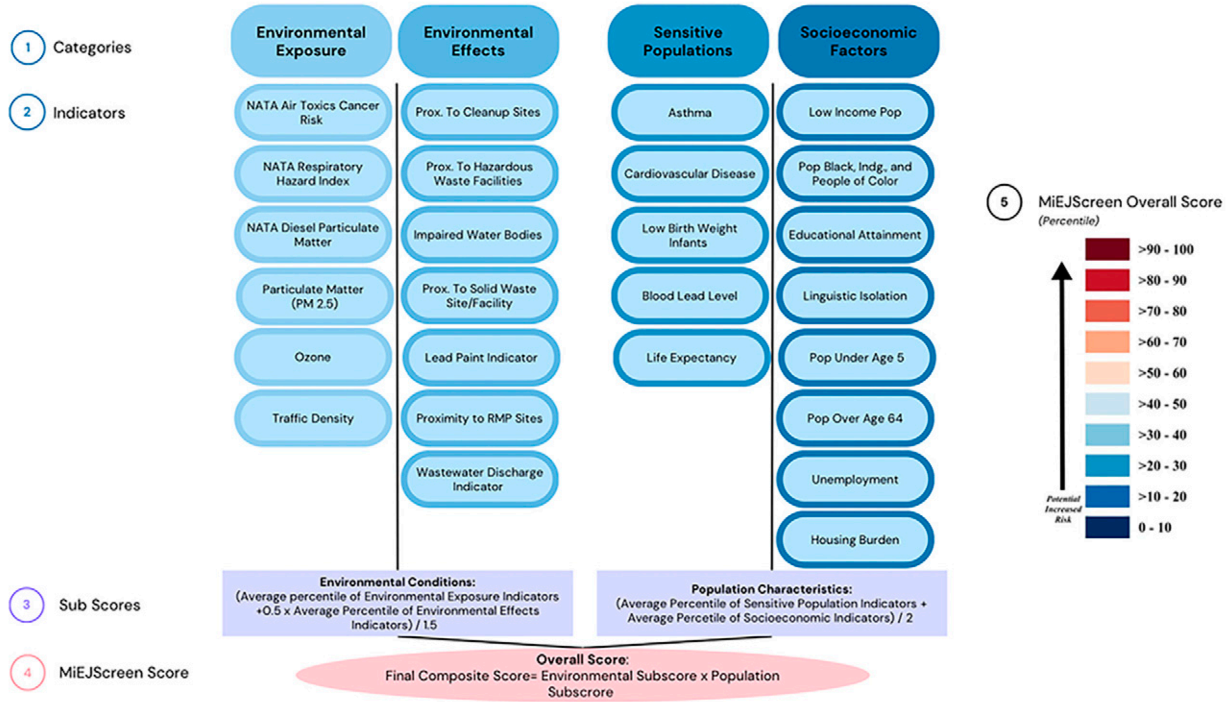

FIG. 2. The MiEJScreen Score is calculated from 26 indicators that are grouped into environmental and population-based categories. Adapted from Michigan Department of Environment, Great Lakes, and Energy, 2022.

used tools developed by the U.S. EPA and Michigan's EGLE. The EPA's EJScreen is a comprehensive EJ screening and mapping tool that provides spatial information on environmental and demographic characteristics to identify areas that may be disproportionately burdened by environmental hazards. EJScreen calculates an overall index from a range of environmental and demographic data. The index is calculated by comparing data at the block group level with regional and national averages. The resulting index provides a relative measure of EJ concerns, highlighting areas where vulnerable communities may face higher environmental risks and potential disparities.

Using the EPA's EJScreen as a model, the state of Michigan began developing the MiEJScreen dataset in 2019. Similar to the EPA's EJScreen, and at the census tract scale, the MiEJScreen tool consists of 26 indicators that are grouped into two major categories as follows: environmental conditions and population characteristics. The environmental indicators include metrics from the National Air Toxics Assessment (NATA) on cancer risk, particulate matter, traffic density, proximity to hazardous waste sites, etc. The population indicators include public health factors such as blood lead levels and life expectancy as well as socioeconomic factors such as income, race, and unemployment levels. Figure 2 shows how the 26 indicators are grouped and used to calculate a final MiEJScreen score. Data used for calculating the MiEJScreen score were calibrated on a scale of 0 to 100. Transforming this information into percentiles makes the input data comparable and combinable.

Percentiles show how local areas compare with countrywide averages in the case of the EPA's EJScreen tool or to other communities across Michigan in the case of the MiEJScreen. As stated in the draft technical report for the MiEJScreen, the overall percentile scores can help to measure relative environmental risk factors in communities, but these scores should not be used as absolute values.[21] As discussed later in this article, standardized quantitative metrics such as MiEJScreen scores can be useful to decision makers, but they have limitations (Fig. 2).

Data analysis

Because data for the different types of wood energy technologies involved different geometries, a mixed-method statistical approach was used to assess how the MiEJScreen data related to the different energy applications. Overall, the main spatial unit of analysis or comparison was the census tract. For the state of Michigan at the time of this analysis, there were 2,767 census tracts. To look at the relationship between the percent of households that use wood as a primary heat source and MiEJScreen data, two types of analyses were completed using ArcGIS Pro: (1) generalized linear regression and (2) geographically weighted regression (GWR). These two regression types were selected based on the results of a local bivariate relationship analysis, and used to understand the overall aspatial relationship between the MiEJScreen indicator data (explanatory variables) and

[21]Michigan Environmental Justice Mapping and Screening Tool: Draft Technical Report, March 2022. https://www.michigan.gov/egle/-/media/Project/Websites/egle/Documents/Maps-Data/MiEJScreen/Report-2022-03-MiEJScreen-Technical.pdf?rev=f9fb3ba3249c4f4aa60ebf6f4d5bbc3a (Last accessed October 27, 2023).

the percent of households relying on wood heat at the census tract level (dependent variable). The stepwise approach to the statistical analysis was done to ensure the results were not outcomes purely of chance. The local bivariate analysis was run iteratively to quantify the trend and structural relationship between dependent (e.g., percentage of wood energy used by census tract) and independent explanatory variables (MiEJScreen overall and subscores). In this test, the statistic (entropy) quantifies if the values of one variable are dependent on or are influenced by the values of another variable and if those relationships vary over space. During this iterative statistical analysis, linear trends, both positive and negative, were consistently highlighted as significant. In fact, for most of the permutations, only such linear relationships were deemed significant. Thus, through these results we saw that the trend and structural relationship were significant (i.e., not the result of chance), but still needing further analysis using regression approaches. For all the statistical analyses, significance was determined using an alpha level of 0.05.

GWR was used to examine how relationships between the explanatory and dependent variables varied across space. GWR recognizes that relationships between variables can differ between locations, allowing for the examination of local spatial patterns with a linear regression approach. By assigning varying weights to observations based on their proximity (i.e., bandwidths) to the target location, GWR produces more accurate and reliable results compared with traditional regression methods that assume uniform relationships across the entire study area. The output for the GWR is vast, including R-squared and Akaike information criterion (AIC). In this study, we highlighted the R-squared as it is a measure of goodness of fit for the overall regression, with values ranging from 0 to 1. This output can be interpreted as the proportion of dependent variable variance accounted for by the regression. To understand model significance, specifically testing the statistical significance of the coefficients, we assessed the pseudo-t statistics. This statistic, developed in ArcGIS during the model runs, had a value that corresponded to a significance level (alpha) of 0.05.

In addition, hotspot analysis was completed within ArcGIS Pro using the optimized hotspot analysis tool. Such analysis executes a Getis-Ord G statistic but uses incremental spatial autocorrelation to determine the ideal distance measure. The incremental spatial autocorrelation uses the Global Morans I statistic with increasing distances, measuring the underlying intensity of spatial clustering at each distance. Local outliers are excluded from analysis. Ultimately features with high or low values cluster spatially based on the z-score and p value. This statistic looks at each value, within the context of the surrounding neighboring features. In this study, the MiEJScreen scores and subscores were used to develop hot spots related to EJ and its influencing factors across the state. Hot spots were those areas with relatively high MiEJScreen scores; cold spots were areas with relatively low MiEJScreen scores.

Commercial wood boilers (n = 118), pellet manufacturers (n = 4), and biomass power stations (n = 8) were all located at particular points within a census tract as opposed to the data for residential wood heat, which was the percentage of households that used wood as a primary heat source within each census tract. To look at relationships between the MiEJScreen data and the locations of nonresidential wood energy technologies, we plotted the locations of commercial boilers, pellet plants, and power stations over the maps showing the results of the hotspot analysis. This type of analysis was selected because the relatively small sample size of each of the larger wood-burning technologies would not allow for statistically grounded regression analysis. For a detailed explanation of the statistical analyses used in this study, see the Appendix.

RESULTS

A map of the overall MiEJScreen Score across the state of Michigan reveals a clear trend: environmental burdens and socioeconomic vulnerabilities tend to be clustered around urban areas in the southern part of the state—most notably in the Detroit area with other hot spots in Flint, Lansing, Grand Rapids, and Kalamazoo (Fig. 3). This overall trend indicates the importance of urban versus rural environments in shaping the results of MiEJScreen analyses. Table 1 shows the average overall MiEJScreen scores for all Michigan census tracts (49.95),

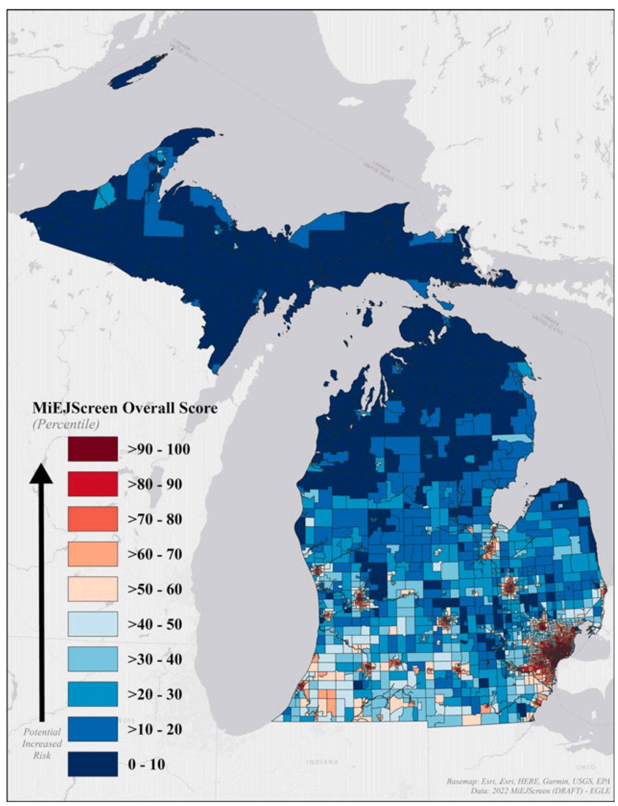

FIG. 3. Overall MiEJScreen scores for the state of Michigan. The spatial units shown are census tracts.

Table 1. Total MiEJScreen Scores Broken Down by Environmental Conditions and Population Characteristics and Reported by Areas That Have Different Types of Wood-Based Energy Technologies. Data from the Michigan Department of Environment, Great Lakes, and Energy, 2022

	MiEJScreen variables–>	*Environmental conditions*	*Population characteristics*	*MiEJScreen score*
All Michigan Census Tracts	Average	49.95	49.95	49.95
	Median	50.00	50.00	50.00
	Largest Value	100.00	100.00	100.00
	Smallest Value	0.00	0.00	0.00
All Lower Peninsula (MI) Census Tracts	Average	51.61	50.64	51.52
	Median	51.90	51.10	51.80
	Largest Value	100.00	100.00	100.00
	Smallest Value	0.00	0.00	0.00
All Upper Peninsula (MI) Census Tracts	Average	40.06	52.72	47.10
	Median	38.95	54.45	46.90
	Largest Value	89.50	98.40	90.90
	Smallest Value	1.40	1.40	4.40
Tracts with > 25% of Households Using Wood for Primary Heat	Average	4.89	48.73	9.33
	Median	4.00	47.55	8.55
	Largest Value	13.60	74.60	21.40
	Smallest Value	0.30	22.30	2.10
Tracts with a Regulated Boiler	Average	24.25	41.44	28.12
	Median	17.10	41.50	22.20
	Largest Value	90.40	95.70	90.90
	Smallest Value	0.30	3.30	0.70
Tracts with a Pellet Manufacturing Facility	Average	26.375	45.725	34.275
	Median	22.35	55.35	35.3
	Largest Value	54.9	68.7	65.5
	Smallest Value	5.9	3.5	1
Tracts with a Biomass Power Station	Average	12.80	51.71	20.20
	Median	7.00	46.75	11.50
	Largest Value	51.00	86.10	76.10
	Smallest Value	2.30	27.50	5.70

census tracts where over 25% of the population relies on wood as a primary heat source (9.33), tracts that have at least one regulated boiler (28.12), tracts that have at least one pellet manufacturing facility (34.28), and tracts that have a biomass power station (20.2). Table 1 also shows environmental and population subscores for these different areas. All locations that have wood energy technologies, which tend to be located in rural places, have scores well under the state average MiEJScreen score. According to the overall MiEJScreen scores, wood energy technologies in Michigan do not appear to be concentrated in areas with existing environmental burdens and socioeconomic vulnerabilities, which tend to be more prevalent in urban places. However, analysis of particular indicators and histories embedded in specific landscapes and communities reveals a slightly more complex picture (Table 1).

Residential applications

Across the state of Michigan, there are 30 census tracts where more than 25% of households rely on wood as a primary heat source (Fig. 4). These households are primarily located in the rural parts of state and represent just over 1% of all Michigan tracts (n = 2,767). As shown in Table 1, of these 30 tracts, the highest MiEJScreen score was 21.40 and the average MiEJScreen score for those areas was 9.33. Although the average median income ($46,847.33) of households within these 30 tracts was lower than the statewide average ($58,596.71) and the percentage of unemployed persons and low-income population was higher that statewide averages, the cumulative score for all population indicators included in the MiEJScreen Tool was 48.73, just under the statewide average. For the environmental indicators used in calculating the MiEJScreen score, these 30 census tracts scored 4.89, well below the statewide average of 49.95 (Fig. 4).

The results of a local bivariate relationship analysis showed a negative linear trend between percentage of households that rely on wood as a primary heat source and the MiEJScreen indicator data. This indicates that as MiEJscore values increase, the use of residential wood energy decreases. However, a generalized linear regression analysis based on continuous data (ordinary least squares or OLS regression) that examined the percentage using households relying on wood heat and the MiEJScreen score showed a weak negative linear relationship, given the coefficient values, with an R^2 of 0.277. Such an R^2 indicates a weaker model in that it accounts for roughly 27% of the dependent variable variance. This

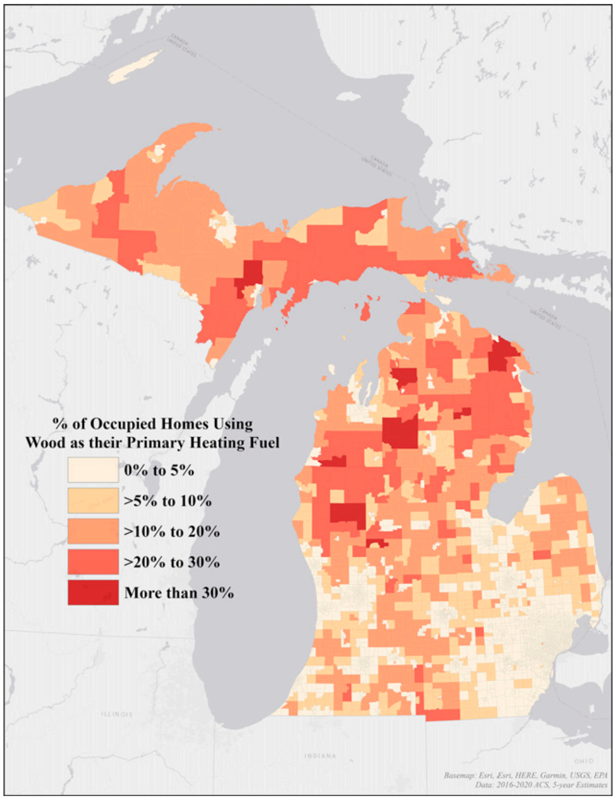

FIG. 4. Percentage of Michigan households that heat with wood.

MiEJScreen model was significant as the alpha of less than 0.05. Given that the MiEJScreen is a merger between two subscores, we used OLS regression to examine trends within each subscore—first for environmental conditions and then for population characteristics.

The relationship between the percentage of households using wood heat and the environmental subscore showed a negative linear relationship and a slightly stronger R^2 value (0.3553). The coefficient values indicate that the negative linear trend was stronger for this second regression compared with the overall MiEJScreen score results. In addition, the environmental subscore was statistically significant. The relationship between the percentage of households using wood heat and the population subscore showed a very weak negative linear trend with an R^2 of only 0.0247. Overall, these results start to show a stronger relationship between the environmental subscore compared with the population subscore.

GWR analysis helps to highlight localized statistical relationships. The results of the GWR that analyzed the relationship between the percentage of households that rely on wood heat and the overall MiEJScreen score showed a spatial trend with an R^2 of 0.475. A GWR analysis was also completed with the environmental subscore indicators. This model was the strongest of those developed with an R^2 of 0.6688. Of the 13 independent environmental subscore indicators included in this model, 6 were statistically significant. Overall, the significant variables showed a negative linear trend in their coefficients and include indicators: NATA respiratory hazard ($R^2 = 0.37$), NATA air toxics cancer risk ($R^2 = 0.37$), NATA diesel particulate matter ($R^2 = 0.38$), ozone ($R^2 = 0.015$, p value $= 0.0499$), and particulate matter ($R^2 = 0.29$).

Overall, the GWR results highlight the driving force of environmental variables rather than population variables in relation to percentage of households that rely on wood heat. In many cases the relationship between the variables was negative and linear, meaning that as the percentage of households that rely on wood heat increased, the independent variables (e.g., particulate matter) decreased. This negative relationship was unexpected, as one might expect to see worse environmental conditions in places where residential wood heat is more common. However, this is consistent with the study's general finding that, according to the MiEJScreen data, rurality may be an important driver of spatial associations as rural areas in Michigan experience fewer air quality concerns than urban areas. Results of regression analyses used to examine trends between residential wood heat and EJ data are summarized in Figure 5.

Commercial boilers, pellet manufacturing facilities, and biomass power stations

Figure 6 shows the locations of regulated boilers, pellet manufacturers, and biomass power stations across Michigan. In addition, Figure 6 highlights the hot and cold spots in relation to the full range of MiEJScreen scores by variables, including (1) the overall EJ score, (2) the environmental variables, and (3) population variables. Such analysis maps show that most of the state's larger wood-burning energy technologies are outside of the EJ hot spots (Fig. 6). Exceptions include a few regulated boilers and the biomass power station located in Flint. When broken down into the subscores, hotspot analysis reveals the powerful influence of the environmental data. Outside of the urban areas in the southern part of the state, the northern lower peninsula is almost entirely in a cold spot and most of the upper peninsula is either not significant or in a cold spot (Fig. 6). Again, these results indicate the importance of rurality in shaping spatial associations between MiEJScreen scores and different types of wood energy technologies.

Similar to the percentage of households that rely on wood heat, the location of commercial wood boilers, biomass power stations, and pellet manufacturing facilities tended to be in northern rural areas where the overall MiEJScreen scores are lower. Of the 99 census tracts that contained at least one regulated wood boiler, the overall average MiEJScreen score was 28.12, environmental conditions were 24.25, and population characteristics were 41.44—all average values were under 50. The only two MiEJScreen indicators that were over 50 for these 99 tracts were "proximity to solid waste sites" and "proximity to cleanup sites." These types of EJ indicators are more common in rural places, as opposed to air quality

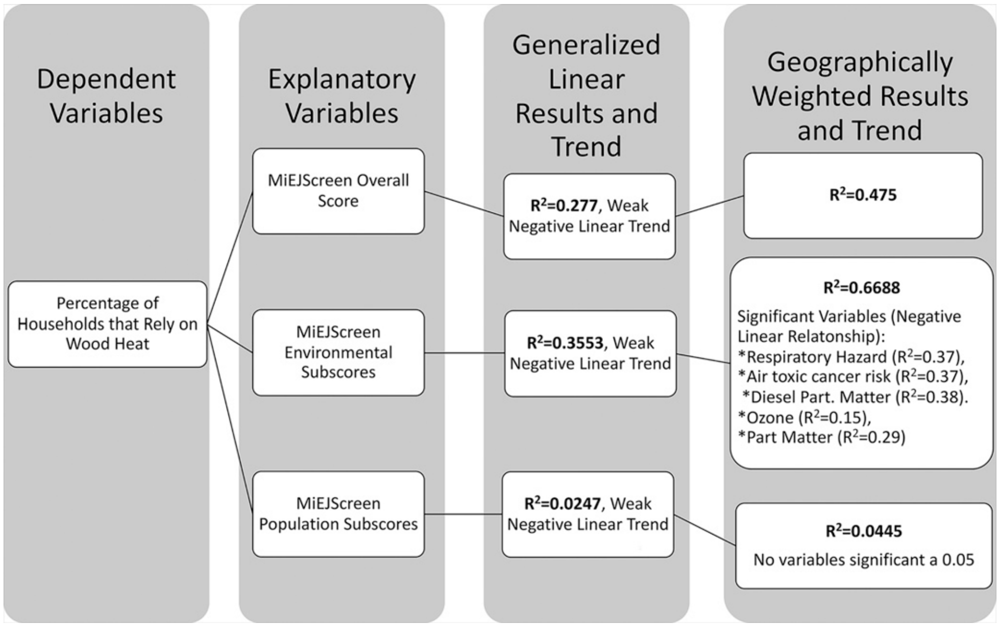

FIG. 5. Results of regression analyses used to examine trends between residential wood heat and EJ data.

and public health indicators that are more characteristic of urban environments.

For all four locations that had a pellet manufacturing facility, the overall average MiEJScreen score was 34.28, with an environmental score of 26.38 and population score of 45.73. Similar to the areas with commercial boilers, places with pellet plants also had values for "proximity to solid waste sites" and "proximity to cleanup sites" that were over 50. In addition, the values for "educational attainment"; "linguistic isolation (percent limited English-speaking households)"; "low-income population composition"; and "unemployed" were all over 50.

Finally, for the eight areas with biomass power stations (or CHP plants), the overall average MiEJScreen score was 20.2, environmental conditions were 12.8, and population characteristics were 51.71. This above-average population score was mostly attributed to socioeconomic variables such as "educational attainment," "low-income population composition," and "unemployed." Similar to commercial boilers and pellet plants, areas with biomass power stations also had

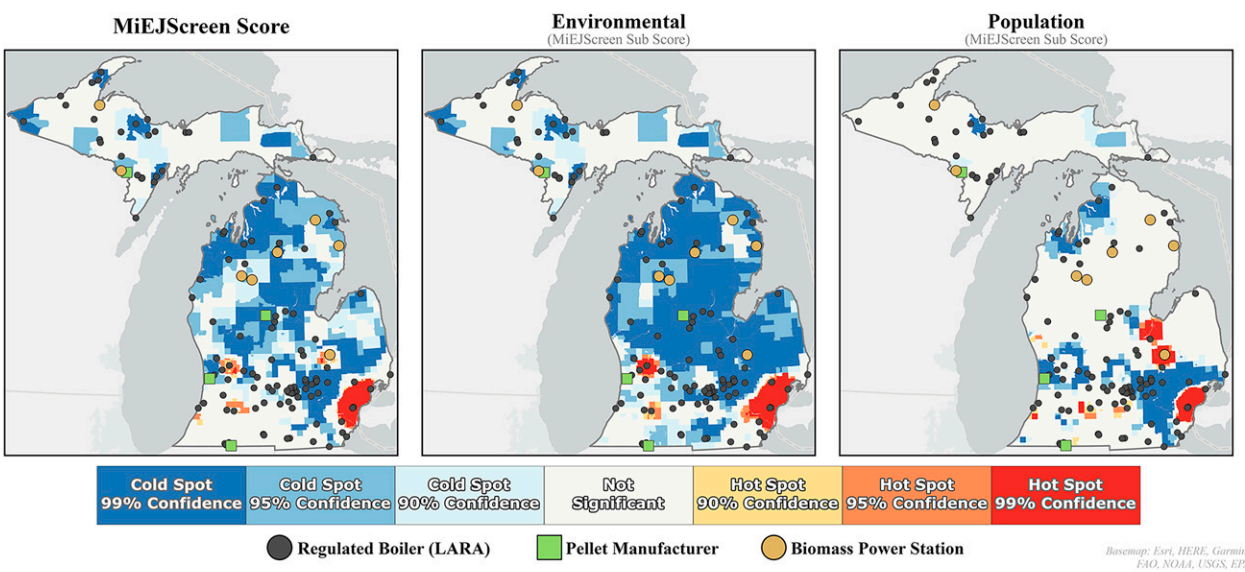

FIG. 6. Hotspot analysis using cumulative MiEJScreen data and subscore data for environmental and population indicators. Cold spots indicate lower concern; hot spots indicate higher concern. According to these data, with a few exceptions, commercial wood boilers, pellet plants, and biomass power stations are located outside of areas of high EJ concern.

values over 50 for "proximity to solid waste sites" and "proximity to cleanup sites."

DISCUSSION

Overall, wood-burning applications in Michigan, including residential wood heating, commercial wood boilers, pellet manufacturers, and biomass power stations, are not clustered in areas that have high cumulative MiEJScreen scores. Hotspot and regression analyses indicate that wood energy at all scales seems to be distributed across the northern part of the state and is not concentrated in environmentally or socioeconomically disadvantaged communities. This finding is consistent with the fact that most wood-burning energy technologies are located within rural, forested communities that may not have active, ongoing air pollution issues.

Results of both the generalized linear regression and GWR indicate that rurality is potentially driving associations. The overall MiEJScreen score is a combination of environmental variables and population variables. The indictors used to calculate the environmental subscore measure issues are more typical of urban environments. Specifically, the environmental exposure category relied heavily on data from NATA, including respiratory hazard data, air toxics cancer risk, particulate matter, ozone, and traffic density. These are all issues that are more common in urban environments as opposed to environmental variables such as proximity to hazardous waste sites or cleanup sites which may be more common in rural places. These findings support the thesis that quantitative datasets such as MiEJScreen are helpful to tease apart different aspects of EJ, but because these tools emphasize variables that tend to be more characteristic of urban environments, they may be insufficient for understanding community dynamics and land-use legacies in rural places. Results of spatial analyses used in this article suggest that more nuanced metrics and methodological approaches may be needed to understand how EJ plays out in rural places.

The MiEJScreen tool calculates a composite score that reflects the complexity of EJ concerns. These types of multivariate approaches can be useful for capturing different aspects of EJ, but in some cases may overshadow particular forms of disadvantage. When indicators such as income and race are isolated, the results of this research seem to support the conclusions of prior studies.[22]

In Michigan, the MiEJScreen score included indicators for race and income among other environmental and socioeconomic indicators. MiEJScreen uses "low-income population," which is a percentage of the population living two times below the federal poverty level. "Race" is a sum of all race/ethnicity categories from the American Community Survey except white/non-Hispanic. As shown in Table 1, the overall average MiEJScreen score for places with pellet manufacturing facilities was 34.3, but when we look at income data alone, we see that three of the four pellet facilities were in places with scores over 50, meaning that these places were in communities with higher levels of poverty than state averages. In addition, the data on race show that one of the four communities with a pellet facility had a score of 82.2, while the other three places were 23.8, 33.1, and 2.5. The small number of places with pellet manufacturing technologies in Michigan, in combination with the other variables used in calculating the overall MiEJScreen score, can result in overall MiEJScreen score averages that obscure important local dynamics.

Pellet manufacturing facilities and biomass power stations were located in areas with higher levels of low-income population, and had higher levels of unemployment than statewide averages. These results suggest that larger scales of bioenergy technologies have different implications for EJ than smaller, more distributed applications such as residential heating and midsize commercial or community-scale boilers. This finding supports the thesis that different applications of wood-based bioenergy have different implications for EJ and is consistent with prior studies. For example, the siting of the biomass power station on the north side of Flint in the 1990s was an archetypal case of environmental injustice when a predominantly African American, low-income community organized to resist the burning of waste wood to generate electrical power for the grid.[23] After a 25-year investigation, the EPA's Office of Civil Rights concluded in 2017 that the preponderance of evidence in the case showed that the state regulatory agency (Michigan Department of Environmental Quality) had discriminated against the predominantly African American community during the permitting process.[24] Although the regression and hotspot analyses showed that wood energy technologies were relatively well-distributed across the state and not clustered in EJ communities, the MiEJScreen tool can help to identify outliers and important local nuances that warrant careful consideration.

Similarly, while the average MiEJScreen score for commercial boilers, pellet plants, and power stations was well below the statewide MiEJScreen average of 49.95, Table 1 indicates that at least one example of all three of these types of technologies was located in a community with high MiEJScreen scores. The highest overall MiEJScreen score for a location with a commercial boiler was 90.9, 65.5 for pellet plants, and 76.1 for power stations. This suggests that the MiEJScreen

[22]Koester and Davis, 2018.

[23]Sarah Mittlefehldt. "Wood Waste and Race: The Industrialization of Biomass Energy Technologies and Environmental Justice." *Technology & Culture* 59 (2018): 875–898.

[24]Lilian S. Dorka, Director, EPA Civil Rights Compliance Office. Letter to Heidi Grether, MDEQ Director, 19 January 2017. www.epa.gov/sites/production/files/2017-01/documents/final-genesee-complaint-letter-to-director-grether-1-19-2017.pdf (Last accessed October 21, 2023).

application can be useful for examining variation between communities to tease apart different dimensions of EJ and injustice.

CONCLUSION

To achieve the ambitious goals of Justice40, policymakers will need data-driven tools such as the EPA's EJScreen and state-level applications such as MiEJScreen. These tools can be helpful for decision makers in trying to understand distributive justice issues related to energy development. However, these quantitative approaches do not account for procedural justice issues, nor do they fully capture community dynamics that are not easily quantified. For example, the map of overall MiEJScreen scores for the state of Michigan seems to indicate that environmental injustice is almost synonymous with increased urbanization (Fig. 3). This study found that the pattern may be caused by the focus on a number of air quality indicators used to calculate the environmental condition subscore. Addressing environmental injustices in urban locations should be a state priority, but the MiEJScreen tool may not fully capture the complexity of what EJ issues look like in rural places, power dynamics involved in decision-making processes, or how different forms of injustice manifest outside of major metropolitan areas. Greater emphasis on how inequity manifests in rural locations is needed, particularly in the context of renewable energy development.

Extractive industries such as mining, logging, and fossil fuel-based energy development have had disproportionate impacts on poor rural communities, and rural communities of color in particular.[25] The legacies of past land use are not particularly well represented in the MiEJScreen data. To address gaps in existing quantitative tools such as MiEJScreen or the EPA's EJScreen, qualitative approaches, focused case studies, and historical perspectives can help to provide a more complete picture of the different forms of disadvantage and inequality. These in-depth qualitative assessments can be used in combination with quantitative models and spatial tools to more effectively characterize community dynamics and to capture a broader range of factors that influence EJ.

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AUTHORS' CONTRIBUTIONS

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Address correspondence to:
Sarah Mittlefehldt
Department of Earth
Environmental & Geographical Sciences
Northern Michigan University
1401 Presque Isle Avenue
Marquette, MI 49855-5305
USA

E-mail: smittlef@nmu.edu

[25]Traci B. Voyles. *Wastelanding: Legacies of Mining in Navajo Country.* (Minneapolis: University of Minnesota Press, 2015).

Appendix: Clarification of Methods and Analyses

Due to the different scales, geometries, and counts of the dependent data, a mixed-method approach was needed to assess how, statistically, the MiEJScreen data related to wood energy utilization. All spatial and statistical analyses were completed within ArcGIS Pro. Specifically, to look at the relationship between percent wood burning utilization and MiEJScreen, two types of analyses were completed: (1) generalized linear regression and (2) geographically weighted regression (GWR). These two regression types were selected based on the results of a local bivariate relationship analysis, also performed within ArcGIS Pro. The two types of regression were completed to see (1) the overall aspatial relationship between the explanatory (MiEJScreen variables) and the dependent variable (% of users relying on wood burning technology at the census block level); and (2) how the relationships between the explanatory and dependent variables vary across space. Conversely, to look at the relationship between the locations of biomass power plants (n = 8), pellet manufacturers (n = 4), and regulated boilers (n = 118) to the MiEJScreen data, hotspot analysis was utilized. This type of analysis was selected to due to low sample size associated with the dependent variable, which would not enable us to develop statistically grounded regression analysis. Instead, we look at the locations of the power plants, manufacturers, and boilers in conjunction with hot and cold spots as it pertains to the MiEJScreen data.

Local bivariate relationship tools were used to analyze local trend patterns using an entropy measure. Given an input of dependent and independent data, this toolset determines, at the local scale not across the whole dataset, if the trends are not significant, positive linear, negative linear, concave, convex, or undefined.

GLR was utilized within the ArcGIS Pro software to model relationships between dependent and independent variables that may not follow a normal distribution. ArcGIS Pro's GLR functionality extends traditional linear regression by accommodating various data types, such as counts (Poisson), continuous (OLS), and binary (logistic) outcomes. This enables users to gain insights into spatial patterns and associations, crucial for making informed decisions. In this study, the OLS approach was used as the dependent data, which was the percentage of those, within a census tract, using wood burning technology.

GWR was also used in ArcGIS Pro to understand the spatial variability when modeling relationships between variables. GWR recognizes that relationships between variables can vary across space, allowing for the examination of local spatial patterns with a linear regression approach. By assigning varying weights to observations based on their proximity (i.e., bandwidths) to the target location, GWR produces more accurate and reliable results compared with traditional regression methods that assume uniform relationships across the entire study area. In other words, GWR constructs separate linear regression equations for every feature in the dataset incorporating both the independent and dependent variables within the optimal bandwidth. The ideal bandwidth is optimized within the GWR analysis using golden search function. The GWR was run on the MiEJScreen indicator data to see which was influencing the spatial trends most strongly. This included separate model runs on all indicator data, environmental subscore indicators, and population subscore indicators.

In terms of GWR parameters, there are multiple ways to develop such models within ArcGIS Pro. First, in terms of model type, there are a wide variety of options ranging from Gaussian to binary; selection is based on the dependent data. For this study, a continuous Gaussian model was developed given that the inputs were continuous in nature. Second, a neighborhood, or bandwidth, is determined to define the distance or number of neighborhoods used for each local regression to be developed. In this study, a distance band was used. The distance band sets the neighborhood size constant for each feature in the study area, which results in more features per neighborhood when feature areas are dense and fewer when they are sparse, similar to a rural/urban trend in our datasets. Lastly, in terms of calculating the distance band, the Golden search options were utilized in ArcGIS Pro. This approach takes the manual determination out of the calculation and determines the best value for the distance band by finding the maximum and minimum distances and tests the AICs at various incremental distances.

Lastly, hotspot analysis was completed within ArcGIS Pro using the optimized hotspot analysis tool. Such analysis executes a Getis-Ord G statistic but uses incremental spatial autocorrelation to determine the ideal distance measure. The incremental spatial autocorrelation uses the Global Morans I statistic with increasing distances, measuring the underlying intensity of spatial clustering at each distance. Local outliers are excluded from analysis. Ultimately features with high or low values cluster spatially based on the z-score and p value. This statistic looks at each value, within the context of the surrounding neighboring features. In this study, the MiEJScreen scores and subscores were used to develop hot spots related to environmental justice and its influencing factors across the state. One thing to note is that a single high value might be of local concern for environmental justice research but may not be a statistically significant hot spot, since it may not be surrounded by other high MiEJScreen values within the neighborhood. We used the resulting spatial pattern of hot and cold spots of MiEJScreen scores and mapped the location of biomass power plants, pellet manufacturers, and commercial boilers. For more information about statistical analyses used in this article, please contact the authors.