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Multiscale Analysis of the Relationship between Toxic Chemical Hazard Risks and Racial/Ethnic and Socioeconomic Groups in Texas, USA

Guangxiao Hu, Kuishuang Feng, and Laixiang Sun*

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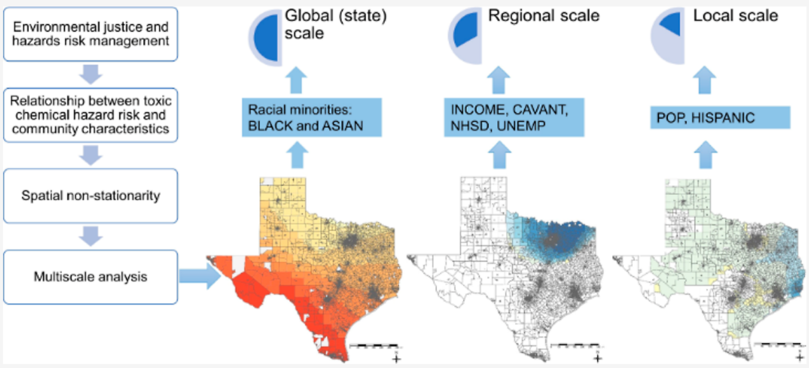

ABSTRACT: Although quantitative environmental (in)justice research demonstrates a disproportionate burden of toxic chemical hazard risks among racial/ethnic minorities and people in low socioeconomic positions, limited knowledge exists on how racial/ethnic and socioeconomic groups across geographic spaces experience toxic chemical hazards. This study analyzed the spatial non-stationarity in the associations between toxic chemical hazard risk and community characteristics of census block groups in Texas, USA, for 2017 using a multiscale geographically weighted regression. The results showed that the percentage of Black or Asian population has significant positive associations with toxic risk across block groups in Texas, meaning that racial minorities suffered more from toxic risk wherever they are located in the state. By contrast, the percentage of Hispanic or Latino has a positive relationship with toxic risk, and the relationship varies locally and is only significant in eastern areas of Texas. Statistical associations between toxic risk and socioeconomic variables are not stationary across the state, showing sub-state patterns of spatial variation in terms of the sign, significant level, and magnitude of the coefficient. Income has a significant negative association with toxic risk around the Dallas−Fort Worth−Arlington Metropolitan Statistical Area. Proportions of people without high school diploma and the unemployment rate both have positive relationships with toxic risk in the eastern area of Texas. Our findings highlight the importance of identifying the spatial patterns of the association between toxic chemical hazard risks and community characteristics at the census block group level for addressing environmental inequality.

KEYWORDS: *environmental justice, multiscale geographically weighted regression, racial/ethnic disparity, spatial non-stationarity, toxic chemical releases, Texas*

1. INTRODUCTION

Technological hazards are an inevitable product of technological innovation and human development.[1] The release of acutely toxic chemicals into the air, water, and land is one type of technological hazard that exerts an impact on climate change,[2−4] ecosystem,[5] and human health.[6−8] The USA Environmental Protection Agency (EPA) defined environmental justice as "the fair treatment and meaningful involvement of all people regardless of race, color, culture, national origin, income, and educational levels with respect to the development, implementation, and enforcement of protective environmental laws, regulations, and policies".[9] Distributive environmental injustice or environmental inequality may occur if certain racial/ethnic or socioeconomic groups experience a disproportionate share of the negative environmental consequences of the industrial activity.[10] There are many screening tools identifying the areas where distributive environmental injustice exists, for example, EPA's EJScreen

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(Environmental Justice Screening and Mapping Tool) provides environmental justice indexes to show areas where vulnerable populations may be disproportionately impacted by pollution. The Council on Environmental Quality proposed the Climate and Economic Justice Screening Tool to identify which communities are identified as disadvantaged based on environmental and socioeconomic indicators. The research on distributive environmental inequality is essential for hazard risk management because it identifies social vulnerability underlying the inequality and thus provides targeting information for risk assessment and mitigation.[11]

Social vulnerability analysis, which is an essential part of the hazard risk management, needs to be considered carefully in order to dedicate appropriate time and resources to specific measures that give the greatest benefits during risk treatment. A general process of hazard risk management includes hazard identification, risk assessment, risk analysis, and risk treatment.[1] Risk identification is a basic stage in risk management, identifying sources of risk hazard factor, peril resources exposed to risk.[12] Hazard risk assessment investigates the potential threat of the identified hazard, including hazard likelihood and hazard consequence.[1] Hazard risk analysis along with vulnerability analysis can help determine the factors that caused the risks, the prioritized ranking of risks, and the reason of the ranking. In the hazard, disaster, and emergency management research, social vulnerability identifies sensitive population that may be less likely to respond to, cope with, and recover from a natural disaster.[13] Social vulnerability is a byproduct of social inequalities, which is influenced by many factors, including income, age, race, culture, and other power relationships.[14,15] Vulnerable people and communities are more likely to suffer from environmental hazards due to varieties of reasons. For example, Fothergill and Peek[16] found that the poor are differentially impacted by hazards due to factors such as place and type of residence, building construction, and social exclusion. Masozera et al.[17] also showed that low-income population are more vulnerable to natural disasters, in the case of Hurricane Katrina, than wealthier ones because the poor live in more hazardous place and have less protection. The findings are similar for other vulnerable groups, such as children and elders,[14,18] and racial and ethnic minorities.[15,19,20] Racial and ethnic minorities are vulnerable to hazards due to the cultural or language barriers that exclude them from communications and action.[17]

The distributive environmental justice literature typically addresses the following 3 W's questions: which vulnerable communities are exposed to environmental hazards disproportionately, where those communities are located, and what are the costs and benefits of risk reduction and management measures.[11,21,22] In terms of technological hazards, racial/ethnic and socioeconomic disparities in hazard exposure in the USA are well-documented (see Table A-1 in the Supporting Information). Some researchers investigated whether exposure to hazardous waste differ by race/ethnicity, age, and other socioeconomic status using statistical analyses.[23−25] Regression models are commonly used to evaluate the relationship between environmental hazards and vulnerable groups, including both global and local models. In a global regression model, all data of the research are used simultaneously to fit a single model, and this type of research implicitly assumes a spatially stationary relationship between explanatory variables and dependent variable(s). For example, Wilson et al.[26] and Naidu et al.[27] used standard econometric regression models to assess spatial disparities in the distribution of toxics release inventory (TRI) facilities and exposure to air pollution by race/ethnicity and socioeconomic status. Their results showed that race was significantly correlated with the distribution of environmental burdens. In fact, most global regression-based research found evidence of racial minorities being disproportionately exposed to pollution.[28−36] In terms of income relevance, this stream of studies found that low-income groups are often disproportionately exposed to pollution.[29,33,37−40] Furthermore, other socioeconomic indicators, for example, home ownership, may also have an effect on the disproportionate distribution of pollution across various race/ethnic and socioeconomic groups.[28,39]

However, the global multivariate regression can hide important local variations in the relationships between environmental hazards and socioeconomic indicators. As EJScreen and other tools show, there is huge heterogeneity between areas where vulnerable populations are impacted by pollution disproportionately. Understanding the spatial heterogeneity of the relationship between environmental hazards and socioeconomic indexes is very important for comprehending the resultant health outcomes at different spatial scales and locations. Considering the spatial distribution of environmental inequality enables policymakers to develop interventions at the local level that target vulnerable groups with the aim to build a health-conductive equal environment.[41] A comprehensive assessment also provides multidimensional perspectives in the environmental justice debates[42] and facilitates the mobilization of local stakeholders.[41] In order to take spatial heterogeneity into consideration, Brunsdon et al.[43] introduced the geographically weighted regression (GWR) model as an extension of general regression models. The GWR is a kernel-weighted regression technique that enables researchers to capture spatial dependence and spatial heterogeneity. The literature has proved that the GWR is a powerful tool for understanding the spatial variations of relationships between environmental conditions, social characteristics, and health inequalities.[44−49] For example, Mennis and Jordan[45] used the GWR analysis and showed that the relationships among race, class, employment, urban concentration, and land use with air toxic release density in New Jersey vary significantly over space. Lersch and Hart[48] and Chamberlain[49] analyzed the relationships between the spatial distribution of industrial facilities and community characteristics in Hillsborough County, Florida, USA, and Houston−Sugarland−Baytown Metropolitan Statistical Area, respectively. Gilbert and Chakraborty[46] and Jia et al.[47] also used the GWR but focused on potential health risks from exposure to hazardous air pollutants that are related to race/ethnicity and socioeconomic status.

However, the GWR operates on a "single bandwidth" for all the variables, and thus, it overlooks the inherent spatial variation in variables that explain negative environmental outcomes associated with environmental injustice within and across geographic units. This limitation can be addressed by multiscale GWR (MGWR), which allows each variable being calibrated at flexible processing scales. In more details, the MGWR specifies the processing bandwidth unique to each variable by considering the underlying spatial unit.[50] The uniqueness is ensured by the MGWR's adaptive Bi-square kernel utility, which removes the effect of observations that fall outside the neighborhood-specified bandwidth and uses the Akaike information criterion (AIC) to select the optimal

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bandwidth for each explanatory variable. Capturing the spatial heterogeneity of environmental inequality by multiple spatial scales can provide perspectives on policy recommendations for specific geographic units. Besides, eliminating the restriction that all relationships hold at the same spatial scale can minimize over-fitting, reduce bias in the parameter estimates, and mitigate the collinearity due to similar functional transformations.[50−53]

To the best of our knowledge, there has been a lack of studies addressing the important question of whether the relationship between negative environmental outcomes and racial, ethnic, or socioeconomic indicators would stay unchanged across multiple spatial scales in the USA. Taking Texas as an illustrative example, this study addressed this gap by investigating the spatial non-stationarity in the associations between toxic chemical hazard risk and community characteristics such as race/ethnicity and socioeconomic status at the census block group level for 2017 using the MGWR. Data on industrial pollution risks are from EPA's Risk Screening Environmental Indicators. Data on income and demographic variables are from the American Community Survey (ACS). In addition to enriching the existing literature on distributive environmental justice and hazard risk management, findings from this paper will provide geospatially explicit information about the relationship between race/socioeconomic status and toxic risk, which can serve as a guidance for intervening in the processes that drive socio-spatial disparity in toxic chemical hazard risks in Texas. The analysis approach of this paper can also be applied to other regions that face similar environmental injustice problems and need more robust hazard risk management.

2. MATERIALS AND METHODS

2.1. Study Area. Texas is the second-largest state in the USA in terms of area and population. It covers approximately 695,662 km^2 of land area with 5265 census tracts and 15,809 census block groups. According to the EPA's 2019 TRI Fact sheet, Texas accounts for about 8.4% of the total number of TRI facilities and about 13% of the total production-related waste managed in the USA.[54] For example, hundreds of petrochemical manufacturing and distribution facilities are located along the Gulf of Mexico and major metropolitan areas such as Dallas−Fort Worth−Arlington and San Antonio New Braunfels, leading to considerable risks of hazardous material releases in the operation or transportation processes, which threaten public safety and human health and damage the natural and manmade environment.

In terms of spatial distribution of population, racial segregation has existed in Texas since the 1820s and was developed as a method of group control after the Civil War.[55] Institutionalized segregation became legalized in places with a large number of Black population and then was extended by the late 19th century.[55] In the 1930s, the Federal Home Owner's Loan Corporation drew maps for nearly 250 cities to document the relative riskiness of lending across neighborhoods, drawing the lowest-rated neighborhoods with a vast majority of African American residents in red (so-called practice of "redlining").[56,57] Cities in Texas, including Amarillo, Austin, Beaumont, Dallas, El Paso, Fort Worth, Galveston, Houston, Port Arthur, San Antonio, and Waco, were included in this program. The economic and racial segregation created by "redlining" persists in many cities.[58] Until recently, the racial inequality still exists in Texas. In 2018, about one in five Black (20%) and Hispanic (21%) Texans were living in poverty, as were 12% of Asian-American and 9% of White Texans. The white unemployment rate in Texas was 3.2% while being 5.3% for Black residents.[59]

The above two sets of significant features of Texas make it an ideal study area for investigating the geospatial patterns of the association between toxic chemical hazard risks and community characteristics at the census block group level, for which the MGWR approach is indispensable.

2.2. Data. The toxic chemical risk data were collected from the EPA's Risk-Screening Environmental Indicators (RSEI) model. The RSEI is a screening-level model, which incorporates TRI data with measures of human exposure and toxicity and assesses the potential impact of industrial chemical releases from pounds-based, hazard-based, and risk-related perspectives.[60] "TRI Pounds" (pounds-based) reflect only the number of pounds released or transferred that are reported to TRI and are available for all releases and transfers. Hazard-based results ("RSEI Hazard" or "toxicity-weighted pounds") are calculated by multiplying the pounds released by the appropriate chemical-specific toxicity weight (the toxicity weight also depends on the exposure pathway), a result that accounts for the size of the release and the chemical's toxicity. A RSEI risk-screening score is calculated as toxicity weight multiplied by the exposed population multiplied by the estimated dose. This research used the RSEI score in 2017 as a dependent variable because it captures the toxic chemical releases, the chemical's toxicity, and human exposure. Because the RSEI score is skewed to the left—many block groups have little or no industrial air pollution—we add 1 (so as to include observations with zero values) and take its logarithm.

According to Galobardes,[61] the socioeconomic status includes the following dimensions: education, housing, income, and occupation-based measures. Thus, the socioeconomic variables we selected include median household income (INCOME), the square of median household income (INCOME2), the percentage of owner-occupied housing (OWNER), the percentage of vacant housing (VACANT), the percentage of adults without a high school diploma (NHSD), the percentage of unemployment (UNEMP), and Gini index (GINI). For racial/ethnic variables, we selected the percentage of Black population (BLACK), the percentage of Asian population (ASIAN), the percentage of other races (OTHERS), and the percentage of Hispanic or Latino (HISPANIC). The variable code names and descriptions are listed in Table 1. All the above demographic data were collected from the American Community Survey (2019 ACS 5-year Estimates).[62] For data cleaning, we removed 46 block groups with 0 population, 604 block groups without median house income data, 1 block group without education data, 1 block group without unemployment rate, and 4 block groups without the Gini index. After cleaning, there remain 15,154 block groups and the statistical summary of the variables is found in Table 2.

2.3. Global Regression Model: the Ordinary Least Squares Model. The equation for the ordinary least squares (OLS) model can be written as

$$y_i = \beta_0 + \beta x_i + \varepsilon_i$$

where y_i is the dependent variable log_RSEI_score in the block group i, β_0 is the intercept; x_i is the vector of selected explanatory variables, β is the vector of regression coefficients, and ε_i is a random error term.

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Table 1. Variable Code Names and Description

variable code name	description
log_RSEI_score	natural logarithm of (1 + RSEI score)
intercept	intercept
POP	population density per square kilometer
BLACK	the percentage of Black or African American population
ASIAN	the percentage of Asian population
OTHERS	the percentage of other races
HISPANIC	the percentage of Hispanic or Latino
INCOME	median household income in the past 12 months (in 2019 inflation-adjusted dollars)
INCOME2	the square of median household income
OWNER	the percentage of owner-occupied housing
VACANT	the percentage of vacant housing
NHSD	the percentage of adults without a high school diploma (for population 25 years and over)
UNEMP	the percentage of unemployment, which is measured by the percent of the labor force that are unemployed.
GINI	Gini index, a summary measure of income inequality, ranging from 0 (perfect equality) to 1 (perfect inequality)

2.4. Local Regression Model: the MGWR Model. The equation for the MGWR model can be written as

$$y_i = \sum_j \beta_{ij}(u_i, v_i)X_{ij} + \varepsilon_i,\ i = 1,2, ..., N$$

where y_i is the dependent variable log_RSEI_score in the block group i; $\beta_{ij}(u_i, v_i)$ refers to the differential bandwidth at the feature space; X_{ij} is the value of the j-th regression parameter; and ε_i refers to the regression error.

To get bandwidth that correctly represents the optimum number of nearest neighbors in the GWR, the adaptive kernel is used to find the optimum bandwidth automatically using the chosen statistical criteria.[63] By allowing multiple bandwidths in the MGWR, the model accounts for an optimal number of neighbors for each parameter estimate, thus allowing better predictions for the response variables, theoretically. The MGWR recasts the GWR as a generalized additive model and uses a back-fitting algorithm, an iterative process of calibrating a series of GWR models based on the models' partial residuals until the MGWR model converges to a solution.[53] The calculation is based on iterations of optimum bandwidth for each parameter estimates.

There are five specifications for five models according to different combinations of explanatory variables. Specification 1 (model 1) only includes population density, race, and ethnicity; specification 2 (model 2) includes population density, race, ethnicity, income, and Gini; specification 3 (model 3) includes population density, race, ethnicity, and socioeconomic indicators except for income; specification 4 (model 4) includes all indicators (exclude NHSD after collinearity test, see Supporting Information Section C); and specification 5 (model 5) includes all indicators (exclude NHSD after collinearity test, see Supporting Information Section C) and income square.

3. RESULTS AND DISCUSSION

Results from all MGWR models are first summarized in order to provide the model fit, significance, and bandwidth of all models in one table (Table 3). Results from OLS models are also provided in Supporting Information Table B-1, which include estimated parameters, model fit, and significance, as a comparison to spatial nonstationary results of MGWR models. More detailed statistical summary and maps of parameter estimates for all MGWR models are presented in Supporting Information Sections D and E. For model performance, local models have higher R^2 values and lower AIC than global models. For example, the R^2 in local models is more than 0.2 in all five specifications, while being less than 0.02 in global models. These sharp contrasts indicate very limited explanatory power of the OLS models. The values of the AIC in local models are around 50,000 for all specifications, while the values in global models are more than 52,600. It means that the

Table 2. Statistical Summary of the Variables (N = 15,154 Block Groups)[a]

	min	max	range	median	mean	SE.mean	std.dev	coef.var
Dependent Variable								
Log_RSEI_score	0.00	17.20	17.20	0.00	0.24	0.01	1.38	5.75
Independent Variables								
Race/Ethnicity								
BLACK	0.00	100.00	100.00	4.40	11.54	0.14	17.20	1.49
ASIAN	0.00	87.51	87.51	0.32	3.73	0.06	7.69	2.06
OTHERS	0.00	90.17	90.17	5.93	9.07	0.08	10.11	1.12
HISPANIC	0.00	100.00	100.00	29.98	38.79	0.24	30.09	0.78
Income								
INCOME	4484	250,000	245,516	56,563	65,600	302	37,186	0.57
GINI	0.10	0.84	0.73	0.39	0.39	0.00	0.08	0.21
Housing								
OWNER	0.00	100.00	100.00	69.14	63.43	0.21	26.41	0.42
VACANT	0.00	92.03	92.03	9.15	11.52	0.09	10.91	0.95
Education								
NHSD	0.00	86.51	86.51	13.63	18.03	0.13	15.63	0.87
Occupation								
UNEMP	0.00	58.74	58.74	3.99	5.26	0.04	5.28	1.00
Other Variables								
POP	0.06	27,721.04	27,720.99	1168.11	1558.19	14.76	1816.63	1.17

[a]Note: SE.mean means standard error of the mean; std.dev means standard deviation; coef.var means the coefficient of variation.

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Table 3. MGWR Results for the Spatial Variability of Parameters Using Adaptive Bandwidth[a]

	model 1			model 2			model 3			model 4			model 5		
	parameter mean	STD	bandwidth	parameter mean	STD	bandwidth	parameter mean	STD	bandwidth	parameter mean	STD	bandwidth	parameter mean	STD	bandwidth
Intercept	−0.034**	0.033	7452	−0.044*	0.239	43	−0.049*	0.241	43	−0.040**	0.038	7452	−0.052*	0.241	43
BLACK	0.039***	0.001	15,153	0.048***	0.001	15,153	0.036***	0.001	15,151	0.031***	0.001	15,151	0.038***	0.000	15,151
ASIAN	0.030***	0.001	15,153	0.035***	0.001	15,153	0.032***	0.001	15,151	0.028***	0.001	15,151	0.033***	0.001	15,151
OTHERS	0.007	0.009	12,793	0.005	0.002	15,153	0.003	0.002	15,151	0.005	0.009	12,793	0.004	0.003	14,632
HISPANIC	0.096*	0.101	1284	0.067*	0.089	1546	0.054*	0.079	1572	0.093*	0.103	1368	0.069*	0.081	1799
POP	−0.256*	0.459	43	−0.186*	0.158	1043	−0.192*	0.159	1067	−0.266*	0.459	43	−0.193*	0.160	1043
INCOME				−0.010**	0.031	9727				0.006	0.020	11,082	0.004	0.035	9890
INCOME2													0.005	0.001	15,151
GINI				0.008	0.016	11,665				−0.004	0.012	11,660	0.004	0.015	11,660
OWNER							−0.030	0.001	15,151	−0.028	0.015	8461	−0.033	0.002	15,151
VACANT							0.006**	0.043	2283	0.001**	0.030	3160	0.006**	0.045	2269
NHSD							0.013**	0.028	4062						
UNEMP							0.006	0.006	12,053	0.007	0.006	12,153	0.006**	0.009	10,064
n	15,154			15,154			15,154			15,154			15,154		
R^2	0.218			0.202			0.205			0.22			0.205		
AIC	41,424.111			41,836.562			41,804.017			41,421.11			41,806.614		
BIC	49,585.467			50,394.597			50,521.595			49,749.02			50,522.124		

[a]Note: "***" means that variables are significant at the global (state) scale; "**" means that variables are significant at the sub-state regional scale; and "*" means that variables are significant at the local scale. Significance in this table means less than 5%.

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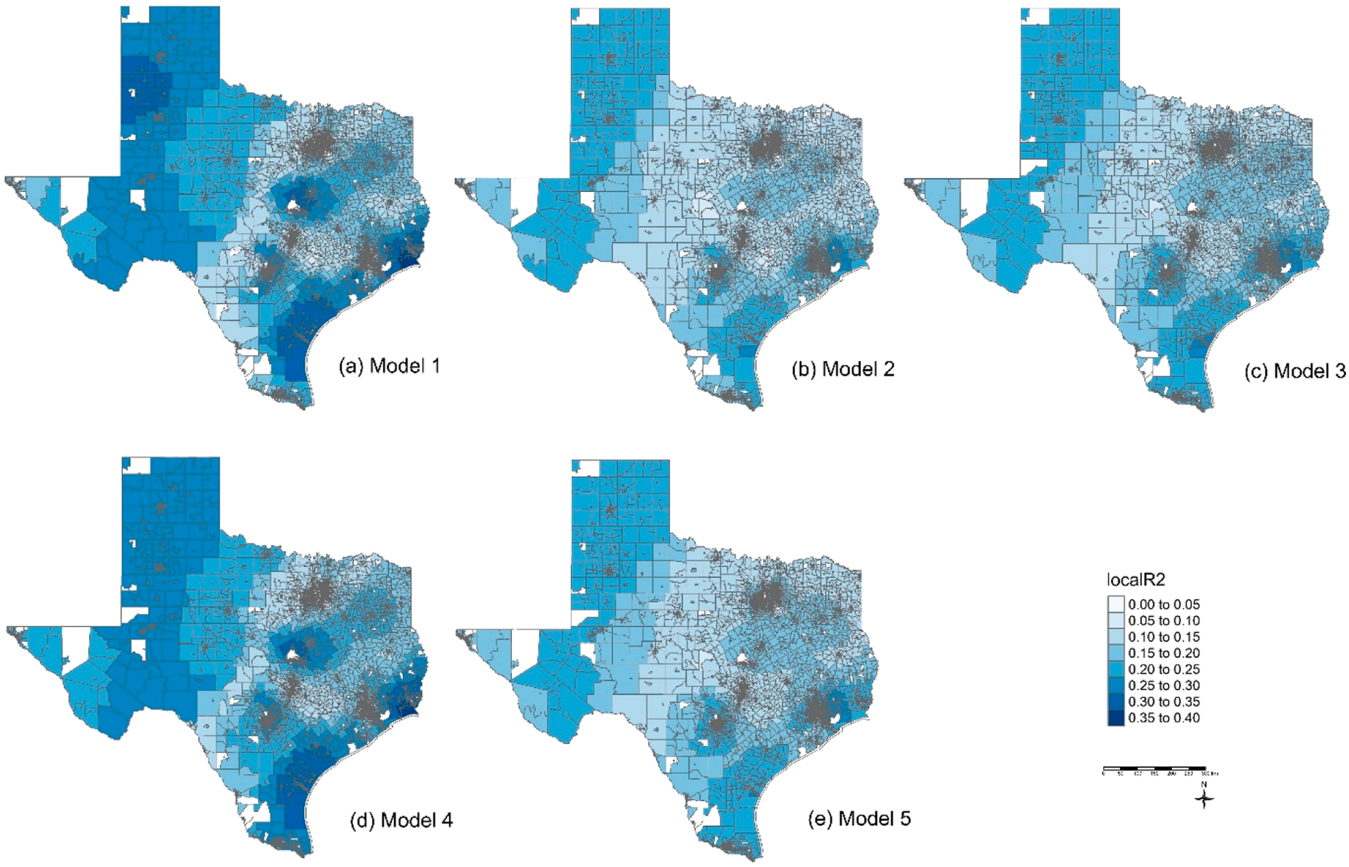

Figure 1. Maps of Local R^2 for all MGWR models. Note: Blocks without color have no data.

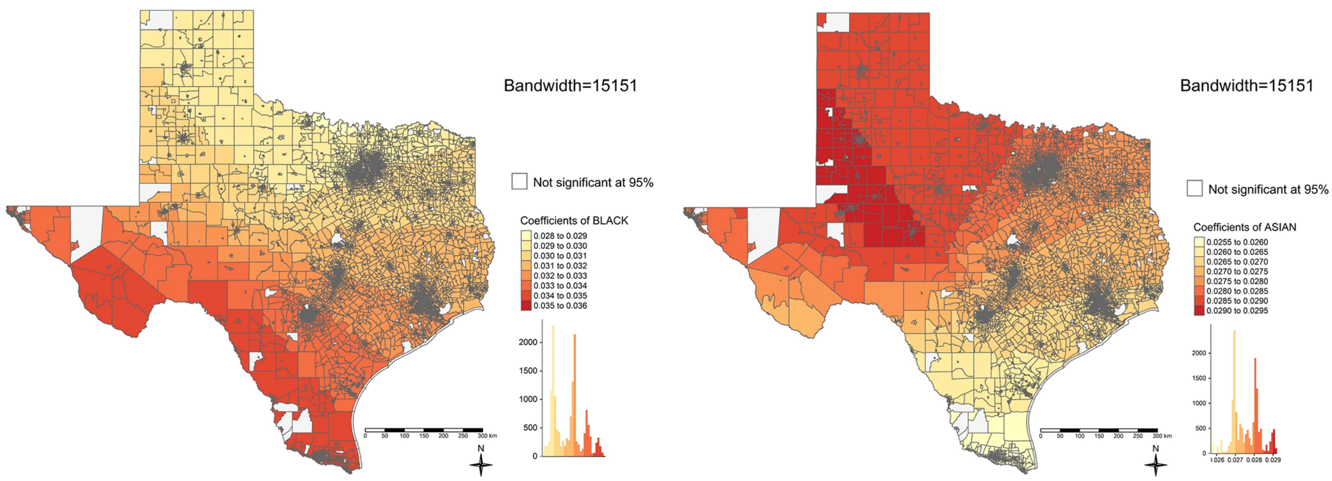

Figure 2. Local coefficients of racial disparity (BLACK and ASIAN) in toxic chemical risk (from model 4). Note: blocks without color have insignificant coefficients or no data.

local models outperform global models. Except for poor model fit for the OLS model, the Moran's I analysis and Monte Carlo simulation (Supporting Information C testing regression assumptions) showed that the RSEI score values are strongly clustered, which means that a global model may cause bias in results due to the omission of spatial characteristics. The high spatial concentration of parameter estimates shown in Figures 2–4 also highlighted the preference for local models.

Among the MGWR models, model 4 has the highest R^2 values and the lowest AIC, indicating that it is the most parsimonious model. Local R^2 values in model 4, also in other models, showed local variations across Texas. Western, southeastern, and central Texas have higher R^2 than other parts of the state (see Figure 1), indicating decent prediction power of the models in these areas. On the contrary, the local R^2 values were low in northern Texas, indicating poor prediction power of the models across these areas. Calibrating a MGWR model produces a vector of optimal bandwidths ("bandwidth" in Table 3, indicating the total number of nearest neighbors) that describe the spatial scale at which each process

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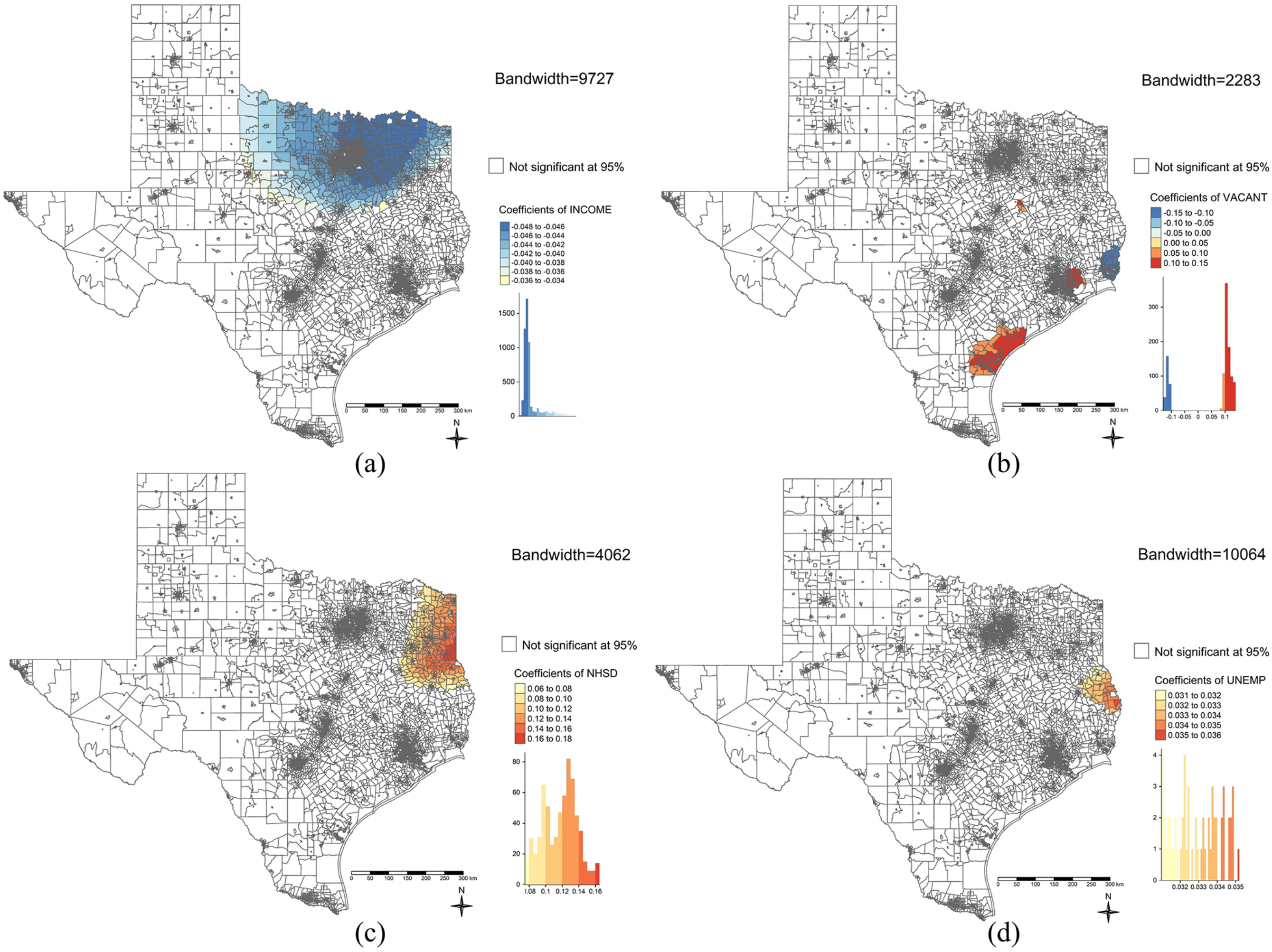

Figure 3. Local coefficients of (a) INCOME (from model 2), (b) VACANT (from model 3), (c) NHSD (from model 3), and (d) UNEMP (from model 5) in toxic chemical risk. Note: blocks without color have insignificant coefficients or no data.

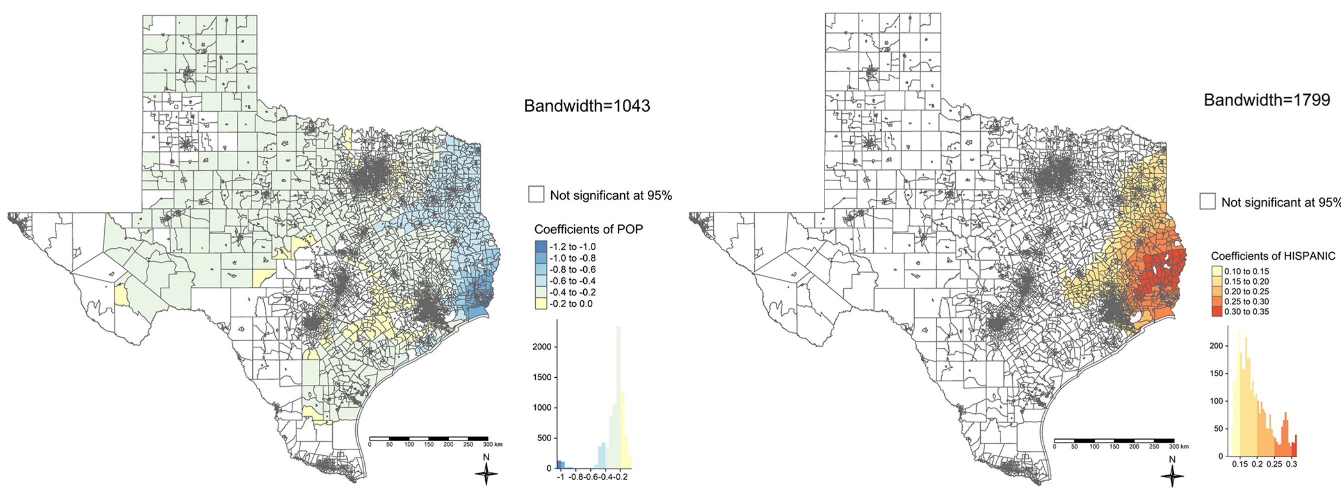

Figure 4. Local coefficients of POP and HISPANIC (from model 5) in toxic chemical risk. Note: blocks without color have insignificant coefficients or no data.

in the model varies.[64] According to the optimal bandwidths of each variable, the relationships between dependent and independent variables for all the models can be explained at the global (for this paper, the state scale), regional (sub-state), and local scales. A global scale means that the bandwidth is large enough to include most block groups in the state when processing the relationships between the response variable and explanation covariates for each location, and thus, the

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corresponding results are statistically consistent across the entire study area. In all models, the parameter estimates for BLACK and ASIAN are significant at the global scale with bandwidths, indicating that most block groups are included in each local subset. In model 2, the parameter estimates for INCOME are significant at the regional scale with bandwidths implying the relevance of several thousand nearest neighboring block groups. Similarly, the parameter estimates for VACANT in models 3, 4, and 5, for NHSD in model 3, as well as for UNEMP in model 5 are also significant at the regional scale. In all models, the parameter estimates for HISPANIC and POP are significant at the local scale, meaning that their relationships with the dependent variable vary locally and the spatial heterogeneity is large. The parameter estimates for OTHERS, INCOME2, and GINI are not significant in any models.

Although Table 3 provides the average parameters for each explanatory variable, regional variations of relationships can be hidden for parameter estimates at the regional and local scale. Further analysis needs to be performed to determine the relationships between racial/ethnic and socioeconomic indicators and toxic risk and how the relationships vary over space, as presented in Figures 2−4. In Figures 2−4, we used sequential color scales to represent parameter estimate values, with warm colors (mainly in red) representing significantly positive, cool colors (mainly in blue) representing significantly negative, and blank representing insignificant parameters or no data.

Figure 2 shows that the racial minorities, including BLACK and ASIAN, have significant positive association with toxic risk at the global (state) scale. These positive associations suggest that densely concentrated racial minority groups are more likely to be exposed to toxic risk in Texas. The coefficients of the BLACK under model 4 range from 0.028 to 0.036 with a mean value of 0.031. It means that holding all other variables constant, with every one percentage point increase in the share of Black population within the block group, the toxic risk would increase by approximately 3.15%. For ASIAN, holding all other variables constant, with every percentage point increase in the share of Asian, the toxic risk will increase by 2.84% (since the parameter mean is 0.028 in model 4).

Figure 2 reveals an important result that even though we used a local modeling technique to analyze the spatially varying relationships between variables, their relationships are consistent over the entire state of Texas. This result resonates with the global model result (see Supporting Information Table B-1) and those in the environmental inequality literature using global models,[26,27,34,35] indicating that the minority racial groups are more likely to experience the negative environmental outcomes. Three complementary explanations have been put forward to analyze these observed environmental inequalities: rational choice, sociopolitical, and racial discrimination.[30] Areas with predominantly minority communities often have cheaper land values, which attracts industry actors to establish polluting facilities because it would be an economically rational choice for them. Sociopolitical reasons take minority communities as the "path of least resistance" because they have fewer resources and political clout to oppose the siting of unwanted facilities, resulting in industries located in those communities.[65] Racial discrimination indicates that minority communities are intentionally targeted for environmental hazards because of beliefs in racial superiority and/or an intention to protect whites from environmental harm.[30,66]

Unlike racial minorities, Figure 3 presents that the statistical associations between toxic risk and socioeconomic variables are not uniform across Texas, showing regional patterns of spatial heterogeneity. From Figure 3, it can be seen that INCOME has a significant negative association with toxic risk around the Dallas-−Fort Worth−Arlington Metropolitan Statistical Area. It means that people with low household income are more geospatially concentrated in these areas with high exposure to toxic chemical risk. In more detail, low-income communities living in block groups around urbanized area in Dallas[67] experience higher toxic risk than their counterparts in rural area nearby (Figure 3). Low-income neighborhoods and communities, similar to racial minorities, are also disproportionately targeted as pollution facilities sites by industries following the path of least resistance. Although previous studies like Chakraborty et al.[28] and Zou et al.[29] using global models showed the same relationships, our result recommends the need for regional-level research in environmental inequality to determine the zooming-in locations with disproportionate distribution of toxic risk.

Other socioeconomic indicators tend to have positive relationships with toxic risk. For example, there are positive relationships between NHSD or UNEMP and toxic risk in the eastern area of Texas. Block groups with lower education attainment (in our study, high percentages of adults without a high school diplomas) are more likely to experience toxic risk, especially in areas around the northeastern area of Texas. High unemployment rates in block groups are also associated with a high level of toxic risk. VACANT has a regional pattern of spatial heterogeneity. There is a negative relationship between VACANT and toxic risk around the city of Beaumont and a positive relationship around the city of Corpus Christi and Houston. This result demonstrates how particular explanatory variables can contribute diversely to toxic risk on different parts of Texas, thus emphasizing the limitation of the global model and the preference for using local models like MGWR to take local processes into consideration.

Figure 4 indicates that the parameter estimate surfaces for population density (POP) tend to exhibit local patterns of spatial heterogeneity. Population density has a negative relationship with toxic risk across northern and eastern Texas, while for western, central, and southern Texas, the relationship is not significant. The absolute values of the parameter estimate in eastern Texas are larger (up to −1.2 to −1) than in other regions like northern Texas (less than −0.4). Population density is a commonly used control variable in the environmental justice analysis.[28,46] Previous research about the effects of population density on negative environmental outcomes, for example, air and water pollutants, toxic materials, and greenhouse gases, has generated contradictory results. For example, Borck and Schrauth,[68] Naidu et al.,[27] and Chakraborty et al.[28] showed that higher population density tends to associate with more air pollution, environmental risk, and health risk. However, Li et al.[35] found that excess emissions are negatively correlated with population density. Gilbert and Chakraborty[46] indicated a significantly positive influence of population density on cancer risk in Tampa, and an opposite effect in Jacksonville, meaning that the relationships are different in different areas. The unequal distribution of the relationship across Texas in our study, together with the contradictory results from previous studies, emphasizes the need to conduct detailed spatial analysis in determining the

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relationship between population density and toxic risk across geographical locations.

According to the United States Census Bureau, Hispanic or Latino are officially the nation's largest minority group, accounting for 18.4% of the USA total population in 2019, whereas this share is up to 39.3% in Texas. Unlike the racial minorities like Black and Asian people, which experience consistent relationships with the toxic risk over the entire state of Texas, the relationships between the ethnic minorities Hispanic or Latino and the toxic risk are not stationary across Texas. Instead, the pattern of the relationship varies locally and is only significant in certain areas, such as eastern Texas. The percentage of Hispanic or Latino has a positive relationship with toxic risk in eastern Texas, with the parameter ranging from 0.1 to 0.35. The estimates around major town Beaumont are larger than that in other surrounding areas. This may be partly because Hispanics are often segregated or constrained to rent homes in neighborhoods that are disproportionately exposed to multiple types of environmental externalities and pollution.[28,69]

To summarize, this study analyzed the spatial non-stationarity in the associations between toxic chemical risk and community characteristics including socioeconomic status, race/ethnicity, and population density across census block groups in Texas, USA, in 2017. It employed the MGWR technique to investigate whether the direction and extent of the associations vary spatially at different geographical scales in the state. The results showed that vulnerable racial minorities, measured as the percentages of Black or Asian population in a census block group, have significant positive relationships with toxic risk and the relationships remain stationary across the state, which means that racial minorities are exposed to high toxic chemical risk wherever they locate in Texas. Unlike racial minorities, the statistical associations between toxic risk and socioeconomic variables are not stationary across the state, showing regional patterns of spatial variation. Income has a significant negative association with toxic risk around the Dallas−Fort Worth−Arlington Metropolitan Statistical Area, meaning that low-income communities are more geospatially concentrated in these areas with high exposure to toxic chemical risk. The share of the population without high school diplomas and the unemployment rate both have positive relationships with toxic risk in the eastern area of Texas. This means that people with low socioeconomic status are more geospatially concentrated in eastern areas with high exposure to toxic chemical risk. There is a negative relationship between the percentage of vacant housing and toxic risk around the city of Beaumont, while this relationship is positive around the city of Corpus Christi and Houston. The relationship between toxic risk and the population share of ethnic minority Hispanic/Latino varies locally and is only significantly positive in eastern areas of Texas. Population density has a locally varying relationship with toxic risk, and the relationship is significantly negative in northern and eastern Texas.

The findings of this study provided evidence that supports the environmental justice movement.[46] The movement was started by people of color to address the inequity in the distribution of environmental protection, including exposure to toxic chemical hazards by various communities. Vulnerable minorities, especially African Americans, Asians, and Hispanics/Latinos, were disproportionately affected by toxic chemical hazards in Texas, the riskiest state in the USA according to the rank of the RSEI risk-screening score in 2019. Our findings further highlight the importance of identifying the spatial patterns for addressing environmental inequality in Texas. This more spatially explicit analysis can be extended to other states with a high level of toxic chemical risk.

The results of this study provide useful information for identifying hot spots with disproportionate toxic risk and thus facilitating better-targeted hazard risk management. In other words, with the detailed zoomed-in information on the distribution of disproportionate toxic risk across geographical locations and diverse communities, the policymakers such as the Texas Environmental Agency and Texas Department of State Health Services can better identify the combinations of the most vulnerable locations and communities for targeted monitoring and mitigation, thus more effectively reducing the disproportionate impacts of toxic chemical hazards on most vulnerable communities and improving environmental health and well-being of all residents. For example, our finding indicates that racial minorities are exposed to high toxic chemical risk wherever they locate in Texas; thus, it would be more useful to implement a state-wide policy in order to manage racial injustice regarding toxic exposure. On the other hand, a more local-level policy would be more useful when it comes to managing toxic exposure of income inequality. Although the EJScreen tool can also provide highlighted areas with higher environmental injustice, it lacks information on the statistical relationships between toxic chemical hazards and racial/ethnic and socioeconomic indicators. This paper provided information on how the direction and extent of the associations between hazards and socioeconomic indicators vary spatially at different geographical scales, which would provide policymakers with evidence to tackle the real-world situations at various scales, ranging from the census-block neighborhood to the state level.

Furthermore, the geographically specific findings of this study imply that a broader constellation of actors at the county, town, and village levels needs to be involved in environmental justice planning or engagement, in addition to a few agencies at the state level or in big cities. The detailed presentation and reasoning of the spatial patterns for environmental inequality provided science-based information and academic support that will empower the community stakeholders in their push to achieve environmental justice at the local level. This spatial-explicit information can help emergency managers and urban planners to identify which part of their community is more vulnerable to technological hazards and further help them to better prepare for, respond to, and recover from actual damage and casualties resulting from the hazardous substance events.

Nonetheless, our study could be strengthened by addressing some limitations. First, our study only used the RSEI score as a measure of toxic risk, which may present a certain extent of uncertainty. RSEI incorporates information from EPA's TRI database, which tracks certain toxic chemical releases and waste management activities at federal facilities and larger industrial facilities across the USA and its territories.[60] Other exposures, for example, exposure to transportation and occupational exposure, are needed to be considered in future studies. Second, our study conducted a cross-sectional spatial analysis only on the relationships between toxic chemical risks and the distributions of the socioeconomic status, racial, and ethnical minorities, further research needs to be performed for the spatial−temporal features of environmental inequality across varying geographical scales. Third, our study used toxic risk data from the RSEI model, which contains the toxic

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chemical releases, the chemical's toxicity, and human exposure. However, toxic chemical releases have adverse impacts on people's health, from acute poisonings and events to chronic effects like cancer and non-cancer potential.[6,8] Health impacts of toxic chemical releases need to be considered in future analysis of environmental inequality study.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c04302.

Literature review of distributive environmental inequality in the USA; the OLS model results for the spatial stationarity of parameters; testing regression assumptions, including distribution of the dependent variable, linear relationship, normality of residuals, testing the homoscedasticity assumption, multicollinearity, Moran's I analysis, and statistical tests for MGWR results; MGWR parameter statistical summary; and parameter estimates for all models (PDF)

Parameter estimates for models 1−5 (XLSX)

■ AUTHOR INFORMATION

Corresponding Author

Laixiang Sun − *Department of Geographical Science, University of Maryland, College Park, Maryland 20742, United States; School of Finance & Management, SOAS University of London, London WC1H 0XG, U.K.;* orcid.org/0000-0002-7784-7942; Email: LSun123@umd.edu

Authors

Guangxiao Hu − *Department of Geographical Science, University of Maryland, College Park, Maryland 20742, United States;* orcid.org/0000-0001-7308-5947

Kuishuang Feng − *Department of Geographical Science, University of Maryland, College Park, Maryland 20742, United States;* orcid.org/0000-0001-5139-444X

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.2c04302

Notes

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