Exploring the Environmental Justice Implications of Hurricane Harvey Flooding in Greater Houston, Texas

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Objectives. To assess the environmental justice implications of flooding from Hurricane Harvey in Greater Houston, Texas, we analyzed whether the areal extent of flooding was distributed inequitably with respect to race, ethnicity, and socioeconomic status, after controlling for relevant explanatory factors.

Methods. Our study integrated cartographic information from Harvey's Inundation Footprint, developed by the US Federal Emergency Management Agency, with sociodemographic data from the 2012–2016 American Community Survey. Statistical analyses were based on bivariate correlations and multivariate generalized estimating equations.

Results. The areal extent of Harvey-induced flooding was significantly greater in neighborhoods with a higher proportion of non-Hispanic Black and socioeconomically deprived residents after we controlled for contextual factors and clustering.

Conclusions. Results provide evidence of racial/ethnic and socioeconomic injustices in the distribution of flooding and represent an important starting point for more detailed investigation of disproportionate impacts associated with Hurricane Harvey.

Public Health Implications. Our findings highlight the need to prepare for and address the unequal social consequences of climate change-related disasters, which are expected to increase in frequency and severity. (*Am J Public Health.* 2019;109:244–250. doi: 10.2105/AJPH.2018.304846)

See also Galea and Vaughan, p. 196.

The literature on distributive environmental justice encompasses a wide range of quantitative studies that seek to determine if socially disadvantaged individuals are disproportionately affected by environmental health hazards and their sources.[1–3] Although environmental justice research in the United States had traditionally focused on technological hazards (e.g., air pollution and hazardous waste) and concomitant health risks, the devastation caused by Hurricane Katrina in 2005 and the subsequent failure of government to address this disaster prompted researchers to investigate social injustices associated with natural events such as hurricanes and floods.[4,5] Concerns regarding the disproportionate impacts of Katrina on Black and low-income residents of New Orleans, Louisiana, galvanized considerable empirical research on the environmental justice implications of flooding.[4–12] It is particularly important to examine whether socially disadvantaged (i.e., racial/ethnic minority and lower socioeconomic status [SES]) individuals reside in neighborhoods that are adversely affected by hurricane-induced inundation, because floods can cause a wide variety of physical health problems and posttraumatic stress.[13,14]

Most distributive environmental justice studies on floods have adopted a "preflood" approach to examining the sociodemographic characteristics of areas potentially exposed to flood risks, typically measured by using boundaries of designated flood zones. The results have been ambiguous, in terms of statistical relationships between various indicators of social disadvantage and flood risk exposure.[4] Several studies have found socially advantaged groups to experience greater pre-event exposure to flood hazards, compared with disadvantaged populations.[9–12,15] However, environmental justice studies that distinguish between various types of flood zones indicate that socially advantaged individuals are more likely to reside in coastal flood-prone areas than the disadvantaged (unlike inland flood zones) because of water-related amenities such as beach access or ocean views that are unavailable inland.[11,12] Although social inequities associated with the distribution of potential flood risks have been examined, few quantitative studies have focused on the environmental justice implications of actual flood events.

We sought to address this limitation and extend distributive environmental justice research on climate-induced natural disasters through a study that examined disproportionate exposure to flooding caused by Hurricane Harvey in 2017 in the Greater Houston (Texas) metropolitan statistical area (MSA)—one of the most racially/ethnically diverse and populous MSAs in the United States and one severely affected by Harvey. Our objective was to determine whether the areal extent of flooding at the neighborhood (census tract) level was distributed inequitably with respect to race, ethnicity, and SES, after

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controlling for relevant explanatory factors. Our study integrated cartographic information from Harvey's Inundation Footprint, developed by the US Federal Emergency Management Agency (FEMA), with sociodemographic data from the 2012–2016 American Community Survey (ACS). To analyze the environmental justice implications of flooding from Hurricane Harvey, we used generalized estimating equations (GEEs) that accounted for geographic clustering of neighborhoods in the study area and provided statistically valid inferences regarding the relationship between flood extent and both racial/ethnic and socioeconomic explanatory factors.

METHODS

Our study focused on the Houston–The Woodlands–Sugar Land MSA, commonly referred to as Greater Houston, which occupies approximately 26 061 square kilometers in southeastern Texas. As shown in Figure 1, this MSA encompasses 9 counties and is bordered on the southeast by the Gulf of Mexico. Although the official census name is based on its 3 largest cities, this MSA is centered around Harris County, the third most populous county in the United States, which contains the City of Houston. With a total population of about 6.47 million in 2016, Greater Houston is the fifth-largest MSA in the United States and second-largest in Texas. Non-Hispanic Whites account for about 37.8% of the MSA population, with Hispanics (36.4%), non-Hispanic Blacks (16.8%), and Asians (7.2%) representing the largest minority groups.

With regard to tropical storms and hurricanes, Greater Houston has become one of the most vulnerable urban areas in the world, in part because of its proximity to the Gulf of Mexico. Even before Hurricane Harvey, Tropical Storm Allison (2001), and Hurricanes Rita (2005), Katrina (2005), and Ike (2008) all caused widespread flooding. More recently, the Memorial Day (2015) and Tax Day (2016) floods resulted in deaths and substantial property damage. Normal precipitation events have also frequently flooded many neighborhoods in this MSA. Hurricane Harvey struck Texas on August 25, 2017, and resulted in catastrophic flooding caused by record rainfall that severely affected all counties of Greater Houston. A record-setting 76 centimeters of rain fell in parts of this MSA. Recent studies indicate that the magnitude of Harvey's rainfall has become 3 times more likely and 15% more intense because of climatic changes occurring over recent decades.[16,17] More than 156 000 homes were destroyed and at least 70 people died.[17,18] Most flooding receded within a week, but some areas remained flooded for several weeks.[19] According to estimates from a recent analysis of the devastation caused by Harvey, residential structural damages equal $77.2 million and residential contents damages equal $36.9 million in Greater Houston.[20] However, no published study has examined

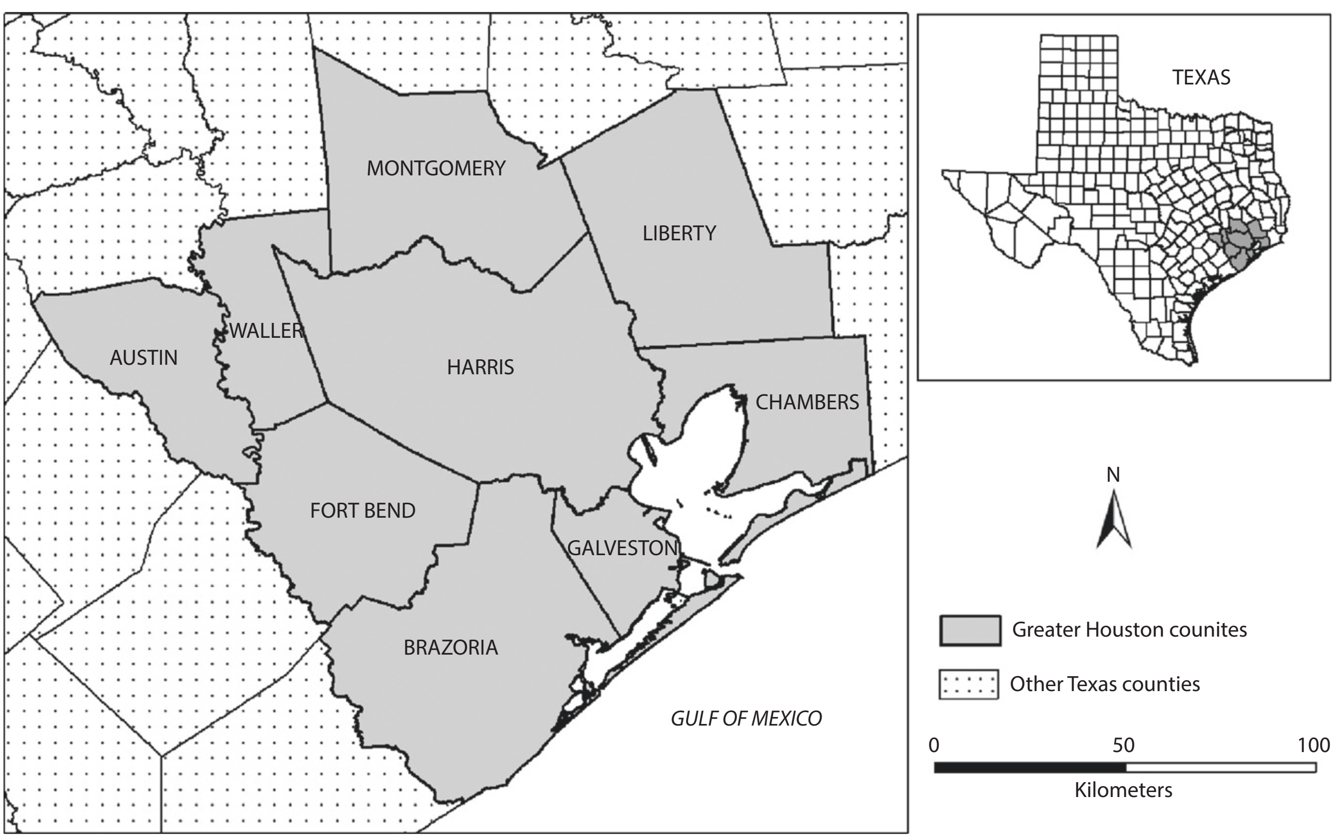

FIGURE 1—Counties of the Greater Houston Metropolitan Statistical Area, Texas

social inequalities in the spatial distribution of Harvey-induced flooding.

Previous environmental justice studies have found significant racial/ethnic and socioeconomic inequities in the distribution of technological hazards such as air pollution,[21–23] toxic waste facilities,[24,25] and accidental releases of toxic chemicals[26] in counties of Greater Houston. Few studies have investigated the environmental justice implications of risks imposed by natural hazards in this urban area. In a comparative study of air pollution and flood risks in Greater Houston,[15] significantly lower percentages of Black and Hispanic residents were found in neighborhoods facing higher 100-year flood risk. This apparent protection of racial/ethnic minorities from flood risk may be due to their inability to afford housing in areas with the water-based amenities that flood zones tend to offer. Another Houston area study[27] used household-level survey data to examine whether Hispanic immigrants are disproportionately exposed to flood risks, after adjusting for a wide range of contextually relevant factors. Their results indicated that 100-year flood risk is associated with being a Hispanic immigrant (compared with other racial/ethnic subgroups), having less property-level flood mitigation, and having lower flood risk perception.

Measurement of Hurricane Harvey Flooding

Our data source for estimating the extent of flooding caused by Hurricane Harvey was a cartographic product referred to as Harvey's Inundation Footprint, which was prepared by the FEMA Region 6 Mitigation Division (TX-DR-4332) to support response and recovery operations.[28] This digital flood inundation grid was derived from a range of federal, state, local, and private sector resources. Specifically, high water marks were obtained from the US Geological Survey, Harris County Flood Control District, federal contractors, and FEMA's Recovery Division to compile a collaborative and comprehensive inventory of known flood depth found throughout the affected area. For this study, we obtained a geographic information system (GIS) raster data set from FEMA's Hazard and Performance Analysis's Geospatial Unit that contains flood depth values (in feet) as an attribute of each grid cell (pixel) and covers all Texas counties affected by Hurricane Harvey.

We estimated the extent of flooding within each census tract in the Greater Houston MSA using a GIS-based methodology that comprised several steps. First, we used a high-resolution version of the National Hydrography Dataset for Texas to remove all permanent water features (i.e., areas containing water during nonflood periods) located within census tract boundaries of counties in this MSA. Second, we overlaid this map layer representing tract land areas (without bodies of water) on the 3-meter by 3-meter resolution Hurricane Harvey inundation raster grid. Third, we counted the total number of pixels with nonzero flood depth values within each tract in our study area. Finally, we calculated the total area covered by these pixels and divided it by the land area of the tract to derive the proportion of the tract area flooded by Hurricane Harvey. We used this areal proportion—referred to as "flood extent" in this article—as a dependent variable in our analysis.

Explanatory Variables

Our distributive environmental justice analysis of Harvey-induced flooding is based on a set of sociodemographic variables from the 2012–2016 ACS for census tracts in Greater Houston. Tracts represent the smallest geographic unit for which reliable 5-year estimates of population and housing characteristics are available from the ACS. To ensure stable proportional estimates for all our variables, we excluded 9 tracts with incomplete data or small population counts. Our study used the remaining 1063 tracts in Greater Houston with at least 500 persons and 50 housing units.

We focused on selecting explanatory variables that are commonly used in distributive environmental justice studies,[1,15,23,29] as well as variables that have been used in research on social vulnerability to flood risks.[4,11,12,30] To examine the effect of race/ethnicity, our analysis included the proportions of individuals who identified themselves as non-Hispanic White, non-Hispanic Black, Asian alone, or Hispanic/Latino, as well as the rest of the tract population (non-Hispanic other races).

To measure socioeconomic characteristics of tracts, we used 5 specific ACS variables: the proportions of the population aged 25 years or older with no high school education, the population aged 5 years or older with limited English language proficiency (i.e., do not speak English very well), individuals with an annual income below the family poverty level (i.e., poverty rate), households with no vehicles available (i.e., zero-car households), and civilians aged 16 and older who are unemployed. These variables have indicated a positive relationship with exposure to environmental hazards in prior environmental justice research.[11,15,22,23,26,29,31] For our multivariate analysis, we combined these 5 variables into a single measure since they were statistically significantly correlated with each other ($0.5 < r < 0.9$). Specifically, we created a robust index of socioeconomic deprivation based on these 5 variables ($\alpha = 0.80$), using principal components analysis. Previous environmental justice studies have recommended the use of such factors because they provide a more nuanced representation of socioeconomic inequality than individual variables, such as educational attainment or poverty status, that are highly correlated with each other.[12,15,31]

We included 2 additional variables that focus on housing characteristics. The first was the proportion of owner-occupied housing units, also known as home ownership rate. This variable has been used in previous environmental justice research as an indicator of wealth and assets.[26,29] The second variable was the proportion of vacant housing units classified as vacant for seasonal, recreational, or occasional use, commonly referred to as vacation homes. Prior environmental justice studies have used this variable as a proxy for water-related amenities and found significantly higher percentages of vacation homes in neighborhoods exposed to coastal flood risks.[11,12]

Statistical Methodology

We first used bivariate correlations to examine statistical relationships between each explanatory variable and the dependent variable. In addition to Pearson's (parametric) correlation coefficients, we also calculated Spearman's correlation coefficients as a nonparametric measure to reduce the effect of outliers. In the second phase, we used GEEs, a multivariate analysis technique suitable for analyzing clustered data, to examine the statistical association between the proportion of tract area flooded and relevant explanatory variables. GEEs have been used in several recent environmental justice studies, including those focusing on Greater Houston.[23,27]

Following Collins et al.,[23] we used GEEs with robust (i.e., Huber–White) covariance estimates, which extended the generalized linear model[32] to accommodate clustered data. GEEs relax several assumptions of traditional regression models, do not require strict distributional assumptions for the variables analyzed, and account for geographic clustering of variables. For this study, GEEs were preferable to other modeling approaches that consider nonindependence of data (e.g., mixed models with random effects). This is because GEEs estimate unbiased population-averaged (i.e., marginal) regression coefficients, even with misspecification of the correlation structure when a robust variance estimator is used, which makes them suitable for analyzing general patterns of inequality across subpopulations.[24,33] Mixed models with random effects, by contrast, generate cluster-specific (i.e., conditional or subject-specific) results that would not provide as reliable an inferential basis for making comparisons across population subgroups.[32] GEEs were also appropriate in our study because the intracluster correlation estimates adjusted for as nuisance parameters are not modeled, as in multilevel modeling approaches.

We used 3 different combinations of explanatory variables in our GEEs. Model 1 focused only on race/ethnicity and included the proportion of the population belonging to the non-Hispanic minority and Hispanic categories. Model 2 included socioeconomic deprivation, home ownership rate, and proportion of vacation homes. Model 3 combined all 7 explanatory variables from both model 1 and model 2.

When estimating a GEE model, one must define clusters of observations under the assumption that observations from within a cluster are correlated, whereas observations from different clusters are independent. Our cluster definition was based on the median year of housing construction for census tracts in the Greater Houston MSA, which we obtained from the 2012–2016 ACS, by county of location. Specifically, we defined clusters of tracts based on median decade of housing construction (2000 or later, 1990–1999, 1980–1989, 1970–1979, 1960–1969, 1950–1959, 1940–1949, and 1930–1939) by county, which effectively resulted in 42 different tract clusters. These tract clusters are depicted in Figure A (available as a supplement to the online version of this article at http://www.ajph.org). The median year of home construction by county cluster definition can be expected to closely correspond with the urban developmental context within which census tracts are nested. Using the median decade of housing to define clusters is also theoretically valid, because it has been documented to match the temporal contextual built-environmental features associated with the historical-geographical formation of environmental inequalities.[24] A similar cluster definition has been used in previous quantitative environmental justice studies using a GEE approach.[23,27,30]

GEEs also require the specification of an intracluster dependency correlation matrix, known as the working correlation matrix. For this study, we specified that the working correlation matrix structure was exchangeable, because this specification assumes constant intracluster dependency.[23,30] To select the best-fitting model, we ran the GEEs multiple times, varying the specifications for each model. Because our dependent variable was continuous with only positive values, we explored normal, γ, and inverse Gaussian distributions with log and identity link functions for a total of 6 model specifications. An identity link function models relationships between the predictors and dependent variable linearly, whereas a log link function represents natural logarithmic relationships between the variables. We selected the normal distribution with log link function for the final GEE models, since this specification yielded the lowest value of the QIC (quasi-likelihood under the independence model criterion), indicating the best statistical fit. Because GEEs do not support model fit statistics that indicate the proportion of variance explained, we provide QIC fit statistics, which are interpretable in a similar manner to the Akaike information criterion as applied to generalized linear models (i.e., smaller values indicate better fit). Although QIC fit statistics are useful for selecting best-fitting models or determining the best link function, they are not directly comparable across the GEEs.

We standardized all explanatory variables before including them in the GEEs to allow direct comparison of model coefficients. We estimated the statistical significance of each individual variable using 2-tailed *P* values from the Wald χ^2 test. To examine multicollinearity, we calculated the condition index for the combination of standardized independent variables in each GEE model. None of our models yielded a condition index higher than 6.0, indicating the absence of collinearity problems.

RESULTS

The spatial distribution of flooding in Greater Houston is depicted as a classified choropleth map in Figure 2. For this map, we grouped census tracts in the study area into 4 quartiles based on the proportion of tract land area flooded by Hurricane Harvey. Tracts in the highest quartile (top 25%) for proportion flooded were located primarily in counties adjacent to the Gulf of Mexico (Brazoria, Galveston, and Chambers) and in the City of Houston in Harris County. Tracts in the lowest quantile were located primarily in the northwestern regions of Greater Houston. The tract-level distributions of 3 key explanatory variables are shown in Figure B (available as a supplement to the online version of this article at http://www.ajph.org). These maps suggest a spatial correspondence between flood extent and the non-Hispanic Black and Hispanic proportions, as well as socioeconomic deprivation, in several counties of the MSA.

Descriptive statistics for all variables and correlation coefficients associated with each explanatory variable are presented in Table 1. In terms of race/ethnicity, flood extent was significantly and positively correlated with the proportion of non-Hispanic Blacks and Hispanics, but negatively correlated with the proportion of non-Hispanic Whites, Asians, and non-Hispanic other race. The socioeconomic deprivation factor, along with the 5 variables that compose this index, were all positively and significantly associated with flood extent. Both home ownership and vacation homes, however, showed a

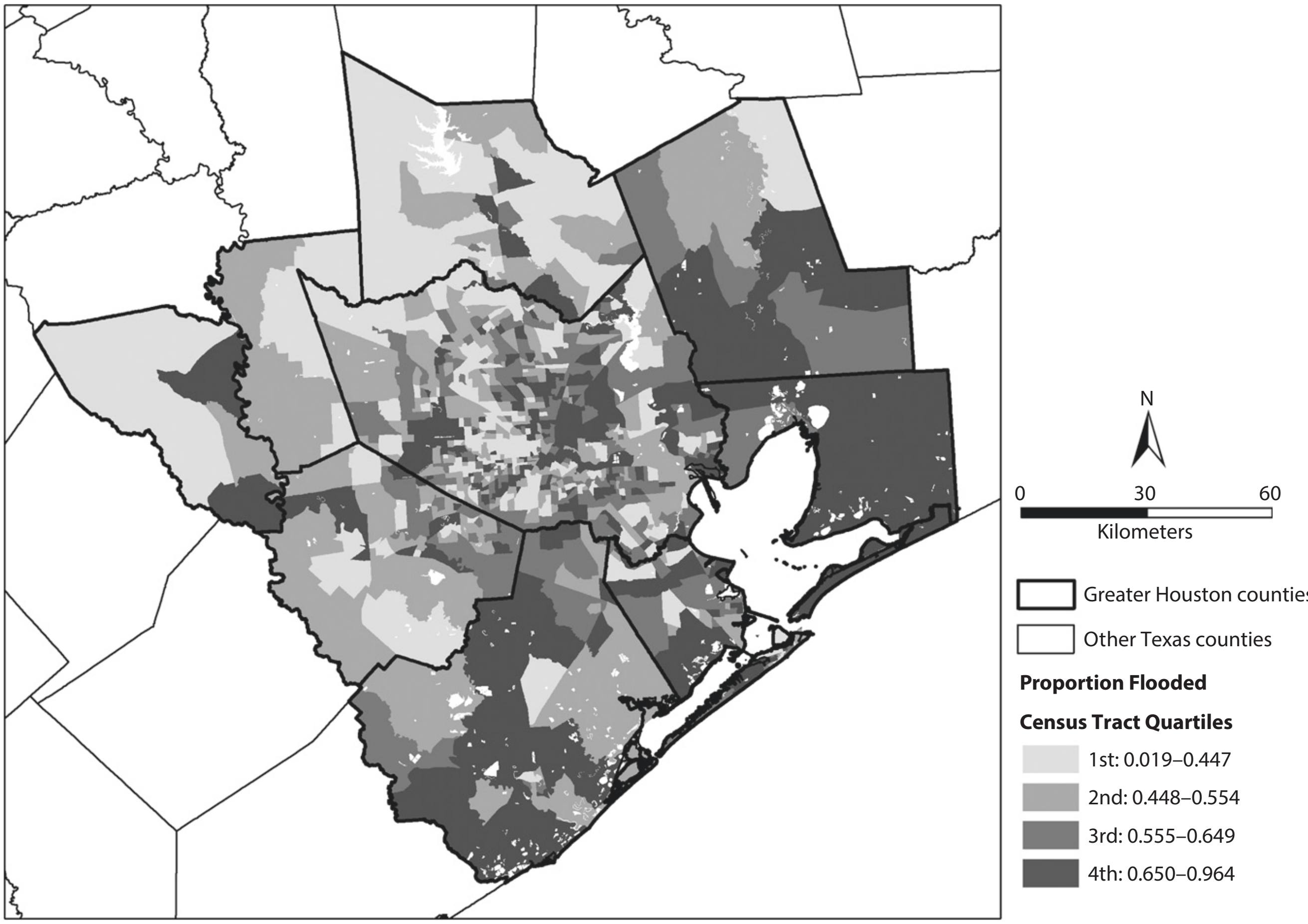

FIGURE 2—Proportion of Census Tract Area Flooded (Flood Extent) by Hurricane Harvey: Greater Houston Metropolitan Statistical Area, Texas, 2017

nonsignificant relationship with flood extent. The values and significance of Spearman's ρ (nonparametric) were consistent with those observed for Pearson's r.

In our multivariate GEEs, summarized in Table 2, we used the proportion of non-Hispanic Whites as the reference group and thus excluded this variable from these models. In model 1, significant and positive coefficients for the non-Hispanic Black ($P < .01$) and Hispanic ($P < .05$) variables indicated that tracts where these subgroups were concentrated had higher proportions of flooded area compared with tracts where non-Hispanic Whites were concentrated. For the proportion of non-Hispanic Blacks, a coefficient of 0.044 with an exponent of 1.045 implies that increasing the non-Hispanic Black proportion by 1 SD led to a 4.5% increase in the mean proportion of tract area flooded, after controlling for the effects of other independent variables. Similarly, increasing the proportion of Hispanics by 1 SD led to a 2.6% increase in the mean proportion of tract area flooded, after controlling for other variables in the model. Model 2 showed significantly higher socioeconomic deprivation and home ownership rates in tracts with greater flood extent ($P < .01$). Increasing socioeconomic deprivation by 1 SD led to a 6.4% increase in the mean proportion of tract area flooded, whereas increasing home ownership rate by 1 SD increased the mean proportion of tract area flooded by 3.3%. The positive coefficient for the non-Hispanic Black proportion remained significant ($P < .05$) after the addition of socioeconomic deprivation and housing variables in model 3. An increase in 1 SD for the non-Hispanic Black proportion led to an increase of 5.0% in the mean proportion of tract area flooded. In the presence of the racial/ethnic variables, socioeconomic deprivation, home ownership rate, and vacation home proportion were all significantly and positively associated with flood extent ($P < .05$) in model 3. An increase in 1 SD for each of these 3 variables increased the mean proportion of tract area flooded by 3.0%, 3.8%, and 2.0%, respectively.

DISCUSSION

We sought to extend distributive environmental justice research on climate change–related disasters by analyzing social inequities in the areal extent of flooding caused by Hurricane Harvey in Greater Houston. Our statistical findings indicate that both race/ethnicity and SES play a persistent

TABLE 1—Summary Statistics for Variables Analyzed and Bivariate Correlations: Greater Houston Metropolitan Statistical Area, Texas, 2017

Variable	Min–Max	Mean (SD) Pearson's r (95% CI)	Bivariate Correlation With Flood Extent: Spearman's ρ (95% CI)	Bivariate Correlation With Flood Extent: Spearman's ρ (95% CI)
Dependent variable				
Proportion of tract area flooded (flood extent)	0.019–0.964	0.549 (0.149)		
Independent variables				
Proportion non-Hispanic White	0.003–0.912	0.370 (0.271)	−0.166 (−0.223, −0.107)	−0.179 (−0.236, −0.121)
Proportion non-Hispanic Black	0.000–0.924	0.173 (0.198)	0.161 (0.102, 0.219)	0.139 (0.080, 0.197)
Proportion Hispanic	0.022–0.989	0.376 (0.245)	0.094 (0.035, 0.153)	0.099 (0.040, 0.158)
Proportion Asian	0.000–0.708	0.062 (0.085)	−0.100 (−0.159, −0.041)	−0.174 (−0.231, −0.116)
Proportion non-Hispanic other	0.000–0.173	0.018 (0.016)	−0.094 (−0.223, −0.107)	−0.099 (−0.158, −0.040)
Socioeconomic deprivation (α = 0.80)	−1.585–4.639	0.000 (1.000)	0.162 (0.103, 0.219)	0.171 (0.1133, 0.228)
Proportion < high school education	0.000–0.667	0.200 (0.154)	0.144 (0.085, 0.202)	0.158 (0.099, 0.216)
Proportion limited English proficiency	0.000–0.763	0.178 (0.150)	0.075 (0.015, 0.134)	0.081 (0.021, 0.140)
Proportion below poverty level	0.000–0.781	0.171 (0.122)	0.113 (0.054, 0.171)	0.142 (0.083, 0.200)
Proportion zero-vehicle households	0.000–0.586	0.065 (0.067)	0.118 (0.059, 0.176)	0.097 (0.038, 0.156)
Proportion civilian unemployed	0.000–0.637	0.253 (0.072)	0.173 (0.115, 0.230)	0.178 (0.120, 0.235)
Proportion owner-occupied housing units	0.000–0.991	0.596 (0.239)	0.003 (−0.057, 0.063)	−0.026 (−0.085, 0.034)
Proportion vacant: seasonal/recreational use	0.000–1.000	0.088 (0.167)	0.003 (−0.057, 0.063)	0.030 (−0.030, 0.089)

Note. CI = confidence interval. There were 1063 census tracts in the sample.

explanatory role in the spatial distribution of flood extent across neighborhoods, even after controlling for housing-related factors and the effects of clustering. Specifically, we found that the Harvey-induced flood extent significantly increased in neighborhoods predominantly comprising Black, Hispanic, and socioeconomically deprived residents. This statistical evidence of distributive injustice associated with flooding in Greater Houston represents an important starting point for more detailed investigation of disproportionate health impacts associated with Hurricane Harvey. Given the well-documented physical and mental health problems associated with flooding,[13,14] racial/ethnic minority and socioeconomically disadvantaged individuals residing in highly inundated neighborhoods are likely to suffer the additional burden of adverse health outcomes.

It is important to consider 2 limitations of this study, which we plan to address in future research. First, we focused only on the areal extent of flooding, not on flood depth, duration, intensity, and other attributes that contribute to adverse health or social consequences. Second, our reliance on neighborhood (tract)-level data

TABLE 2—Generalized Estimating Equations for Predicting Proportion of Tract Area Flooded: Greater Houston Metropolitan Statistical Area, Texas, 2017

	Model 1			Model 2			Model 3		
Variable	B[a] (95% CI)	Exp (B)	Wald's χ^2	B[a] (95% CI)	Exp (B)	Wald's χ^2	B[a] (95% CI)	Exp (B)	Wald's χ^2
Proportion non-Hispanic Black	0.044 (0.025, 0.062)	1.045	21.314**				0.049 (0.028, 0.071)	1.050	20.485**
Proportion Hispanic	0.026 (0.001, 0.051)	1.026	3.583*				0.028 (−0.004, 0.060)	1.028	2.970
Proportion Asian	−0.014 (−0.041, 0.013)	0.986	1.004				−0.008 (−0.032, 0.016)	0.992	0.392
Proportion non-Hispanic Other	−0.011 (−0.030, 0.008)	0.989	1.327				−0.006 (0.025, −0.062)	0.994	0.311
Socioeconomic deprivation				0.062 (0.040, 0.085)	1.064	29.115*	0.030 (0.001, 0.060)	1.030	3.287*
Proportion owner-occupied housing units				0.032 (0.009, 0.056)	1.033	7.377**	0.037 (0.017, 0.058)	1.038	12.555**
Proportion vacant: seasonal/recreational use				0.010 (−0.008, 0.028)	1.010	1.206	0.020 (0.001, 0.039)	1.020	4.063*
Intercept	−0.598 (−0.624, −0.572)		2052.446	−0.601 (−0.626, −0.576)		2237.016	−0.602 (−0.623, −0.581)		3178.916

Note. CI = confidence interval. There were 1063 census tracts in the sample.
[a]Population-averaged estimate; QIC (quasi-likelihood under the independence model criterion) = 39.158 (model 1), 37.271 (model 2), and 43.737 (model 3).
*P < .05; **P < .01.

prohibited examination of whether socially disadvantaged individuals resided within flooded areas and how they were affected by flooding, in terms of home damage, loss of jobs and income, health problems, and other postevent experiences. The use of structured survey or semistructured interviews could help clarify factors influencing neighborhood-level associations and determine whether socially disadvantaged residents were unequally burdened by their disproportionate exposure to Harvey-induced flooding.

Although the adverse impacts of floods have magnified in recent decades because of increases in population and impervious surfaces, climate change has been documented to strongly influence the frequency and intensity of floods and other weather-related hazards.[17,34] Storms that bring more than 20 inches of rainfall in Greater Houston are about 6 times more likely now than they were at the end of 2000, and the annual odds are expected to increase by almost 20% for the period 2081 to 2100.[17] Research on social vulnerability has drawn attention to the amplified risks faced by racial/ethnic minorities and individuals of lower SES from flood-related events, in terms of their constrained access to resources necessary for response, recovery, and medical care.[35] From an environmental justice perspective, understanding and quantifying the unequal social and health consequences of climate-induced disasters are critically important for developing adequate risk management actions, as well as planning adaptation and mitigation strategies. Our findings reveal significant social injustices in the distribution of flooding at the neighborhood level, but more individual- and household-level analyses are recommended to address these objectives. AJPH

CONTRIBUTORS

J. Chakraborty served as the lead data analyst and author. J. Chakraborty, T. W. Collins, and S. E. Grineski obtained the funding for the research and contributed to the organization, writing, and editing of the manuscript.

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Note. Any opinions, conclusions, or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the NSF.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

HUMAN PARTICIPANT PROTECTION

No human participants were used in this research and human participant protection was not necessary.

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