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ORIGINAL PAPER

School vulnerability to disaster: examination of school closure, demographic, and exposure factors in Hurricane Ike's wind swath

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Abstract Damage and destruction to schools from climate-related disasters can have significant and lasting impacts on curriculum and educational programs, educational attainment, and future income-earning potential of affected students. As such, assessing the potential impact of hazards is crucial to the ability of individuals, households, and communities to respond to natural disasters, extreme events, and economic crises. Yet, few studies have focused on assessing the vulnerability of schools in coastal regions of the USA. Using Hurricane Ike's tropical storm wind swath in the State of Texas as our study area, we: (1) assessed the spatial distribution patterns of school closures and (2) tested the relationship between school closure and vulnerability factors (namely physical exposure and school demographics) using zero-inflated negative binomial regression models. The regression results show that higher probabilities of hurricane strikes, more urbanized school districts, and school districts located in coastal counties on the right side of Ike's path have significant positive associations with an increase in the number of school closure days. Socioeconomic characteristics were not significantly associated with the number of days closed, with the exception of proportion of Hispanic youth in schools, a result which is not supported by the social vulnerability literature. At a practical level, understanding how hurricanes may adversely impact schools is important for developing appropriate preparedness, mitigation, recovery, and adaptation strategies. For example, school districts on the right side of the hurricane track can plan in advance for potential damage and destruction. The ability of a community to respond to future natural disasters, extreme events, and economic crises depends in part on mitigating these adverse effects.

Keywords Hurricane Ike · Wind swath · Exposure · Vulnerability · Spatial autocorrelation · Poisson regression · Zero-inflated negative binomial

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1 Introduction

Climate-related disasters can significantly impact communities and their critical social institutions such as schools (Lai et al. 2016). An estimated 700 schools were affected by Hurricanes Katrina and Rita (August and September 2005) (Hurricane Education Recovery Act 2007). Many schools remained closed for months or never reopened after Hurricane Katrina (Kamenetz 2015). After Hurricane Ike in September 2008, schools and other public structures in Galveston were damaged by wind and water (Rifai 2012). Damage to secondary schools amounted to $72 million (Hurricane Ike Impact Report 2008); more than 450 public schools were closed in Texas for 10 or more school days, due to structural or site damage (Texas Education Agency 2009a). After ravaging Haiti and Cuba as a Category 4 Hurricane, Hurricane Matthew made final landfall in South Carolina, causing extensive flooding along the southeastern USA. Schools in Lumberton, North Carolina, were heavily impacted by the floods and closed for several weeks. As of April 2017, one school in particular, West Lumberton Elementary School, remained closed for 7 months after the hurricane (Biesk 2017). In this paper, we focus specifically on hurricanes, which are important to study given that their intensity is expected to increase over time due to climate change (USGCRP 2016). The 2017 hurricane season provided a glimpse of catastrophic impacts to homes, critical infrastructure, and lifelines in Texas, Florida and several Caribbean islands.

When disasters disrupt the functioning of schools, children's academic outcomes, development, and health are threatened, which may, in turn, contribute to a trajectory for a future of weak academic achievement, low educational attainment, reduced income potential, and difficulty in alleviating poverty (Altonji and Mansfield 2011; Convery et al. 2010, 2014; Dunn et al. 2015; French et al. 2014; Herd 2010; Miech and Hauser 2001). Mounting research evidence suggests that children such as these who miss school as a consequence of a disaster may experience new or exacerbated academic difficulties (Scrimin et al. 2006, 2009).

To date, few studies have focused on schools in disaster-affected communities; rather, the focus has been on what happens to children who are displaced and what happens to the functioning of the new school environments where they are transplanted. Thus, the majority of school disaster research has focused on student relocation into schools outside of the communities directly affected by disasters (e.g., Barrett et al. 2008; Meier et al. 2010). The overall results, thus far, find no harmful effect on students who enter new schools and no harmful effects on the overall performance of the schools they have joined. To illustrate, Imberman et al. (2012) found that the influx of more than 75,000 school-aged evacuees from Katrina-affected schools in Houston did not affect the overall level of achievement in Houston schools, which remained steady. However, other studies have demonstrated that on an individual level, changing schools multiple times is associated with negative effects on academic performance for the displaced student (Pane et al. 2008; Sacerdote 2008). This is in line with the associated literature on student mobility and decreased student performance, which finds that changing schools is a stress on children (Engec 2006). The natural experiment of Katrina found many of the children displaced by Hurricanes Katrina and Rita relocated into higher performing schools than the ones they left in New Orleans. In these situations, displaced students often performed better over time (Fothergill and Peek 2015; Hango 2006; Pane et al. 2008; Sacerdote 2008). New Orleans school system was a failing school system before Hurricane Katrina hit, ranking next to last of all of Louisiana's school districts in 2003 (Eisele-Dyrli 2013). The year before the storm hit, 62% of public school students in New Orleans attended a school rated

F by Louisiana (Gladwell 2015). After the hurricane, 102 of the 117 schools in New Orleans were appointed to a special statewide school district, the Recovery School District, which closed failing schools or turned them over to charter school leadership (Layton 2014).

Weber and Peek (2012) and Fothergill and Peek (2015) provide some of the most thorough accounts of the experiences of households with children who were scattered around the country in prolonged states of limbo after Hurricane Katrina. In referring to children, Fothergill and Peek (2015, p. 25) warn us that "in understanding the concept of cumulative vulnerability, it is important to keep in mind that it has a temporal component, in that vulnerability unfolds over time. But it also has an additive component: the more that risk factors accumulate, the more likely children are to experience developmental delays, poor mental or physical health, or negative educational outcomes."

Despite the important role of schools in all aspects of daily life, few studies have focused on examining educational attainment and outcomes vis-à-vis post-disaster school recovery trajectories in disaster-prone communities and regions. Specifically, post-disaster vulnerability assessments and risk analyses have not focused on schools, their location, downtime, student composition, and exposure to climate-related hazards. In order to address the dearth of research on schools in disaster-affected communities, this paper focuses on schools affected by Hurricane Ike.

Using Hurricane Ike's tropical storm wind swath in the State of Texas as our study area, we focus on two research aims: (1) assessment of the spatial distribution patterns of school closures in hurricane Ike's wind swath impact area and (2) testing of the relationship between school closure and vulnerability factors (namely physical exposure and school demographics). The article begins with a literature review as context for linking the concepts of disasters, vulnerability, and school recovery and educational attainment, as well as appropriate regression methods for measuring the relationship between school closures and vulnerability. This is followed by a study area section which includes information on the impact of Hurricane Ike in the State of Texas, as well as school district demographics, historical hazard damage, and historical hurricane strikes and exposure variables. The next two sections present the methods and results from our exploratory cluster analysis and zero-inflated negative binomial regression models. The explanatory variables in our models account for the fact that school districts have a differential exposure to the hurricane throughout our large study area, which encompasses 60 counties and 294 school districts. The final section presents a summary of the interesting or surprising insights and findings, potential contributions, and research limitations.

2 Literature review

The severity of the impact of disasters on schools and their curriculum and educational programs depends on a host of factors: physical vulnerability, school structural integrity, socioeconomic vulnerabilities of students and their families, household displacement, and recovery timeframes of households and communities. This section summarizes a subset of scholarly work with important insights and frames of reference for linking the concepts of disasters, vulnerability, school recovery, and educational attainment and for informing the selection of variables and methods.

2.1 Vulnerability factors likely to be associated with school closures and school recovery

Vulnerability is a multidimensional construct captured in both pre-event and post-event demographic and socioeconomic dimensions, and physical dimensions (including exposure); it is a well-covered construct in the disaster research literature (see, e.g., Dow and Downing 1995; Cutter et al. 2003; Thomas et al. 2013; Wisner 2016). Socioeconomic and demographic vulnerability refers to the inability of people, organizations, and societies to fully withstand adverse impacts to hazards. Traditional socioeconomic and demographic risk indicators include poverty, age (i.e., children, elderly), female gender, disability, housing tenancy (e.g., owner-occupied vs. rentals), disadvantaged status, minority racial status, and low educational attainment (Cutter et al. 2003, 2010; Laska and Morrow 2006; Peacock 2010; Esnard et al. 2011).

Several scholars have found that economically and socially disadvantaged persons are more likely to reside in housing that is substandard and more likely to be damaged during weather disasters, public housing, or rental housing (Peacock and Girard 1997; Fothergill and Peek 2004; Myers et al. 2008). At the community level, GIS technology can be used to map and analyze patterns of physical and socioeconomic vulnerability, with the caveats that disasters can have differential impacts on households and that vulnerability is not a static phenomenon. Overall, the physical and social vulnerability of communities to climate-related disasters is an important determinant for forecasting the length of school closure, and the pace of school recovery. The repeated exposure of houses, critical infrastructure, and social institutions needs to be addressed as well, particularly in hazard-prone areas (Birkmann and Welle 2015).

Exposure is further exacerbated given the expansion of "capital stock"—lifeline infrastructure, such as transportation networks, electrical networks, water networks, and other critical facilities—in hazard-prone areas (Mileti 1999). More recent scholarship, including that by Holand (2015, p. 1), has couched lifeline infrastructure in a social vulnerability framework by defining lifeline vulnerability as "those aspects of social vulnerability to natural hazards that are influenced by lifeline failure."

2.2 Methodological approaches: focus on regression models

Scholars who work with disaster and natural calamity data have used ZIP and ZINB regression models to better understand vulnerability and exposure factors that are associated with damage, fatality, health outcomes, and other adverse outcomes after disasters (Zahran et al. 2008; Heid et al. 2016). Zahran et al. (2008) compiled SHELDUS data on flood fatalities in Texas for the period 1997–2001 to examine casualty outcomes at the county level. Using ZINB regression models, they found that the odds of flood casualties increase with level of precipitation on event date, flood duration, property damage, population density, and presence of socially vulnerable populations (Zahran et al. 2008, p. 537). Using ZIP regression models, Heid et al. (2016) sought to understand factors, such as demographics, social support, and storm exposure, that influence development of post-traumatic stress symptoms in older adults after Hurricane Sandy. Storm exposure data in that case were collected from individuals as part of the ORANJ BOWL (Ongoing Research on Aging in New Jersey—Bettering Opportunities for Wellness in Life) research panel study.

Heid et al. (2016) found that greater storm exposure was linked to higher levels of post-traumatic stress symptoms. However, levels of social cohesion moderated this relationship such that this relationship was attenuated among individuals who reported higher levels of social cohesion. Beyond understanding such associations, ZIP and ZINB models have also been used for modeling and simulation purposes. Beckett et al. (2014) estimated parameters of a ZIP regression and applied these parameters to model past disasters. While the application of ZIP regression has value for disaster researchers studying a range of phenomenon, Guikema and Quiring (2012) caution about applying such models in the disaster risk assessment and complex infrastructure systems performance domains. They used the example of power outage and customer meter outage forecasting models to make the case for their novel hybrid classification tree/regression method, also applicable to other complex, zero-inflated datasets (Guikema and Quiring 2012). The tree/regression method proved to work well when thresholds for the zero outcomes exist and are homogeneous for all observations, but not necessarily in real-world applications (Guikema and Quiring 2012).

3 Study area and variables

> Due to its abnormally large size, Hurricane Ike impacted a wide area, accompanied by strong winds and heavy rainfall which created huge waves and extensive surges (Kim et al. 2016, p. 407).

Hurricane Ike made landfall in the USA in Galveston, Texas, on September 13, 2008, as a Category 2 hurricane, with sustained winds of 110 mph, and destructive storm surge across the upper Texas and southwest Louisiana coast (Overpeck 2009; National Weather Service 2014). Tornado activity associated with Hurricane Ike was also reported, but confined to areas east and northeast of Southeast Texas (Overpeck 2009). As of April 2017, Hurricane Ike was the fourth costliest hurricane disaster to affect the USA, after Hurricanes Katrina, Superstorm Sandy, and Hurricane Andrew (Costliest U.S. Natural Disasters 2014). The most damaging impacts of Hurricane Ike were to the Houston/Galveston area, with the most severe wind, storm surge, and flooding localized on the urbanized barrier island of Galveston (Brody 2012; Houston–Galveston Area Council 2012; Peacock et al. 2012; Texas Department of Public Safety 2013).

3.1 Hurricane Ike’s wind swath

Hurricane Ike had a large wind field that covered a broad area of southeast Texas. Tropical storm force winds were felt inland as far north as the city of Longview which is partially located in two northeastern Texas counties (Harrison and Gregg counties) (Overpeck 2009). A comparative study by Czajkowski and Done (2014) of damage losses from Hurricanes Ivan and Dennis (both Category 3 hurricanes that made landfall is 2004 and 2005, respectively) provides evidence of factors such as wind duration (and not simply maximum wind speed) as important contributors to the magnitude of losses which extended far inland. Therefore, the tropical force wind swath provides a good approximation of the area impacted by a storm. We use Hurricane Ike's tropical storm[1] wind swath in the State of Texas as our study area (Fig. 1), which encompasses 60 counties and 294 school districts. The Texas school districts were selected if their centroids fell within the wind swath, although we recognize that school districts vary in size, and impacts are specific to portions of each impacted school district.

3.2 Texas schools and school districts affected by Hurricane Ike

Schools and other public structures in Galveston were damaged by wind and water from Hurricane Ike. In Galveston, Texas, where Hurricane Ike made landfall, student enrollment fell by 20% immediately after the hurricane, largely due to families evacuating the region. This led to unintended consequences of lower school operating budgets and teacher layoffs (Texas Engineering Extension Service 2011), which further decimated schools' institutional infrastructure. Beyond Galveston, more than 500 public schools were closed in Texas for ten or more school days due to structural or site damage (Texas Education Agency 2009c). Figure 2 shows the spatial distribution of school closure days in the study area.

We focused on the school district as the unit of analysis, rather than individual schools, due to the availability of data. The 294 school districts were closed for a range of zero (0) to nineteen (19).[2] The frequency of closure data following Hurricane Ike in Texas is summarized in Table 1. Of the 294 school districts, 55 districts were closed for 10 or more school days, with 23 closed for 11 or more days. These 55 districts alone encompass 623 campuses (366 elementary schools, 138 middle schools, and 119 high schools). This is an extensive period of unplanned school closures following a disaster for a large amount of schools. In comparison, a combined 2845 schools in the entire USA were closed during the 2011–2012 and 2012–2013 school years as a consequent of a natural disaster (Wong et al. 2014). Of these unplanned closures, 63% of schools ($n = 1790$) were closed for 1 day, 14% of schools ($n = 391$) were closed for 2 days, 4% of schools ($n = 114$) were closed for 3 days, and 19% of schools ($n = 550$) were closed for four or more days (Wong et al. 2014).

3.3 Socioeconomic and demographic variables

We identified four (4) demographic variables and one (1) socioeconomic variable at the school district level for the school year immediately preceding Hurricane Ike (i.e., 2007–2008): percent Hispanic, percent White, percent Black, percent Other (Asian and Native American), and percent economically disadvantaged. The trends for these variables by school district by year are shown in Fig. 3. Economically disadvantaged includes children who are receiving free or reduced-price lunch, programs under Title II of the Job Training Partnership Act (JTPA); food stamp benefits; Supplemental Nutrition Assistance Program (SNAP); Temporary Assistance to Needy Families (TANF); and Pell grant or comparable state program of need-based financial assistance (Texas Education Agency 2009b). School district demographic data were compiled using publicly available from Texas Education Agency (TEA) resources. The TEA provides access to Academic Excellence Indicator System performance reports for each Texas public school and district for 2003–2004 through 2011–2012.

We also reviewed the spatial patterns of the school districts which have majority Hispanic and majority economically disadvantaged student populations. The maps show an

[1] Tropical storm minimum sustained wind speed is 34 miles per hour (NOAA 2017).

[2] Mean 3.6, standard deviation 4.2.

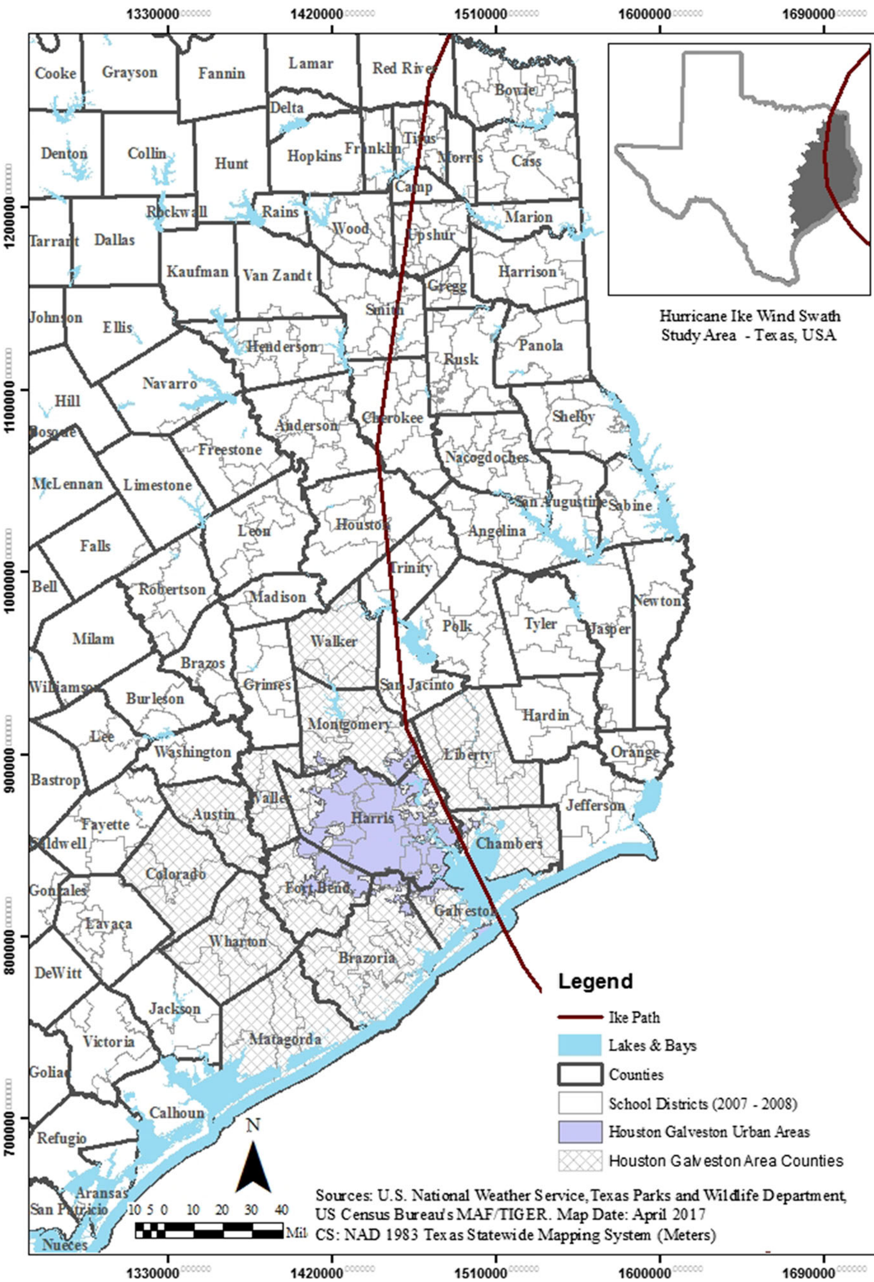

Fig. 1 Map of east Texas study area which includes 60 counties and 294 public school districts during the 2007–2008 Texas school year. Thirteen (13) counties within the Houston/Galveston metropolis are identified as well as the path of Hurricane Ike

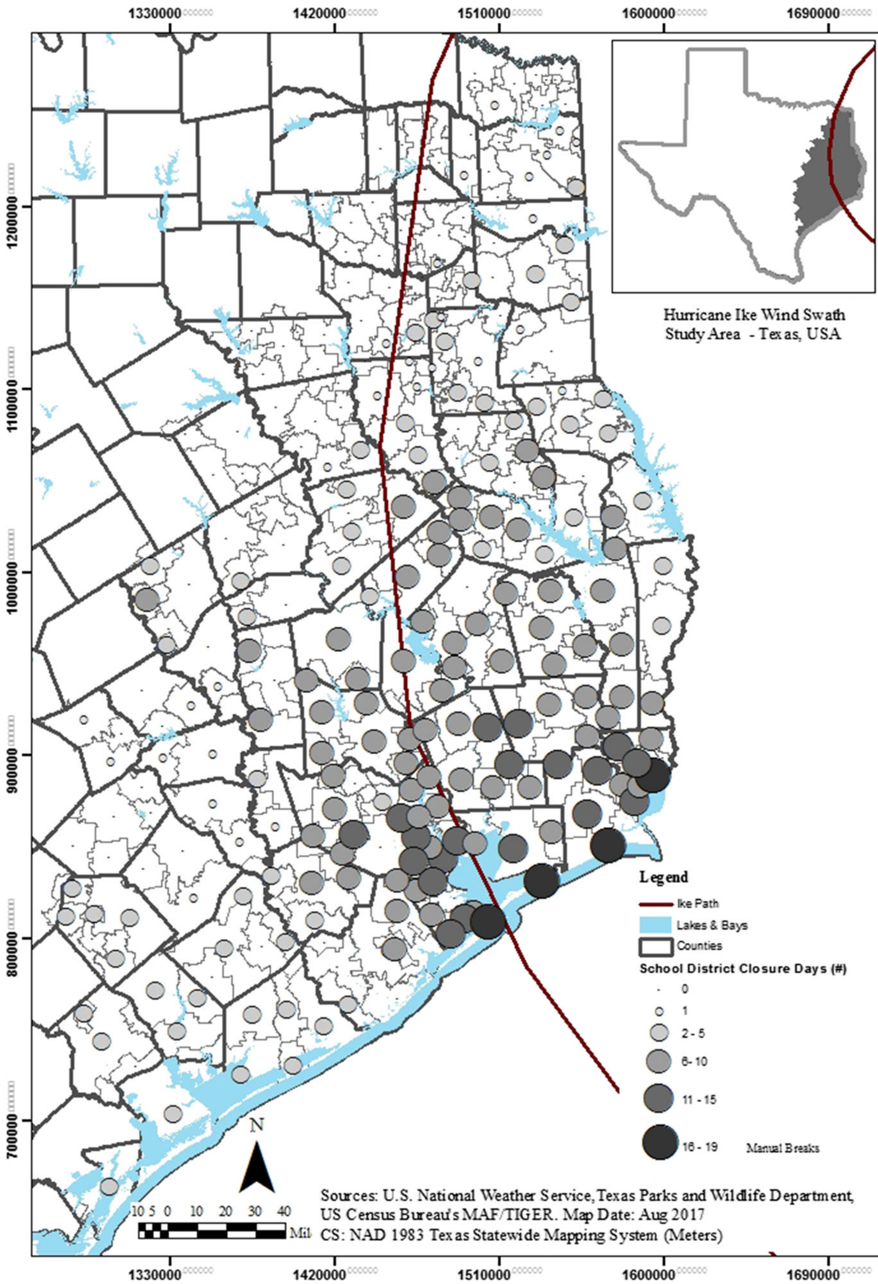

Fig. 2 Distribution of school district closure days (gray circles) relative to the Hurricane Ike path and distance from coastal landfall

even distribution of economically disadvantaged school districts throughout the study area, but a concentration of Hispanics in the southwestern section of our study area (see Fig. 4 for the latter).

Table 1 Frequency of school days closed

Days closed	Frequency
0	112
1	28
2–5	59
6–10	72
11–15	19
16–19	4
	$n = 294$

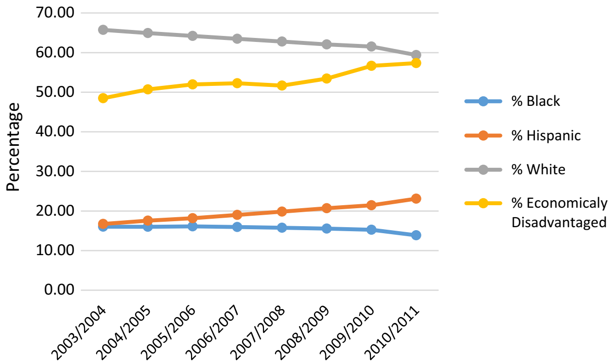

Fig. 3 School district demographic characteristics (2003/2004–2010/2011). *Note* Focus is on three largest ethnic groups

3.4 Physical vulnerability: focus on exposure

Disasters can produce effects on people as well as infrastructure. We control for physical vulnerabilities, historical hazard exposure, and hurricane return periods.

3.4.1 Historical hazards and losses

In our study area, there were three disasters which rose to the level of FEMA disaster declarations during the period 2003–2012: Tropical Storm Erin in 2007, Hurricane Ike in 2008, and the 2011 Wildfires. FEMA distributed a total of \$57,100 (mean = \$9516) in home and property disaster loans for Tropical Storm Erin, a total of \$435,024,100 (mean = \$763,200) for Hurricane Ike, and a total of \$2,223,400 (mean = \$58,511) for the 2011 wildfires (FEMA 2016).

The Spatial Hazards Events and Loss Database for the United States (SHELDUS), a county-level hazard database provided more detailed data on property and crop losses, injuries, and fatalities for events from 1960 to present (http://hvri.geog.sc.edu/SHELDUS/). We focused on adjusted total (and per capita adjusted to 2014) property damage and total fatalities by year rather than by county level (Table 2), because SHELDUS typically distributes the losses for multi-county events equally across the affected counties (HVRI 2016, p. 14). To understand historical hazard exposure, we summed the fatality and damage data by year, from 2003 to 2013, to account for pre-and post-Ike disaster impacts from flooding, hail, thunderstorms, hurricanes, storms, hurricanes, and, wind, and tornados for the 60 counties in the wind swath (Table 2).

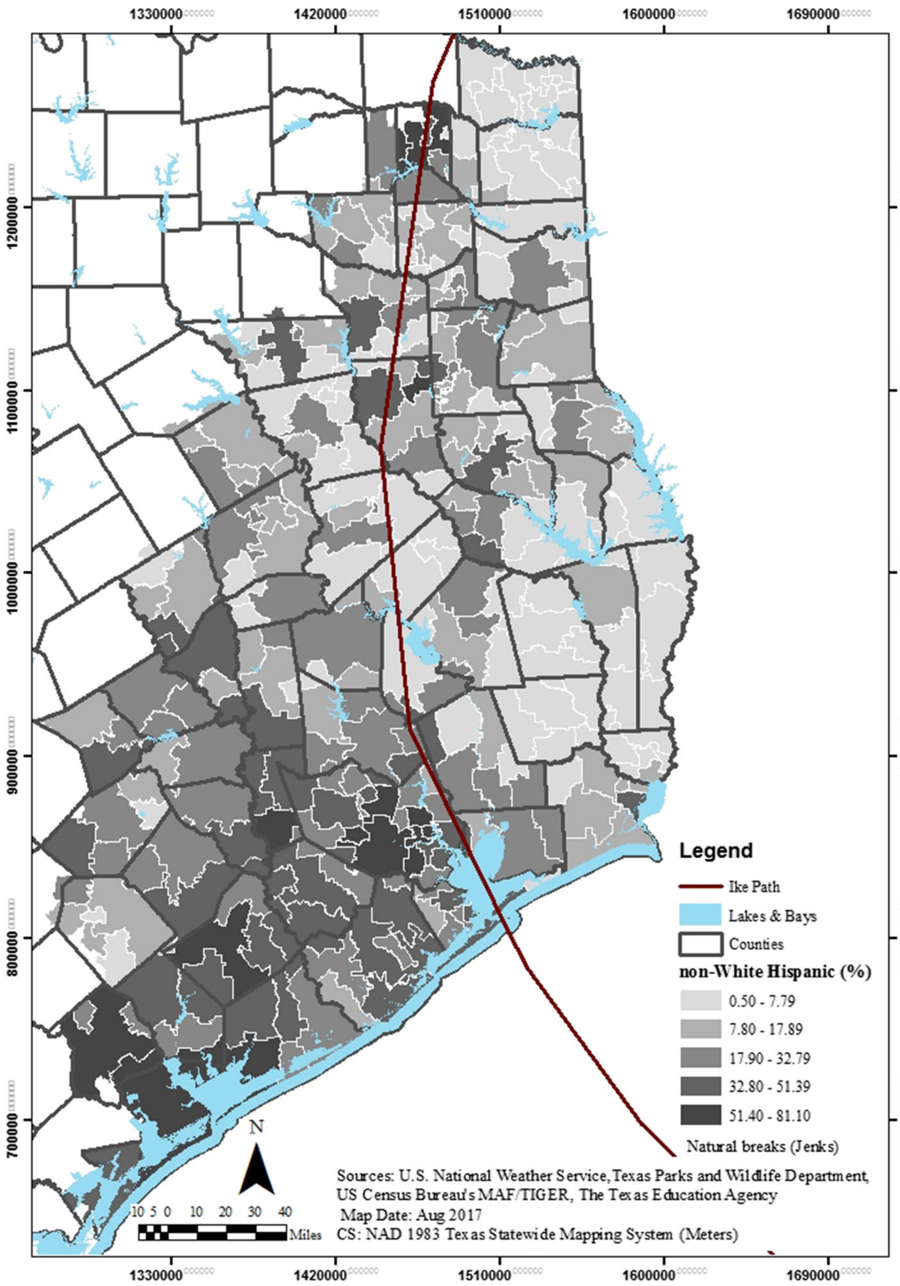

Fig. 4 Spatial distribution of Hispanic school-aged children in school districts

3.4.2 Hurricane return periods

It is also important to understand the frequency of hurricane strikes that have impacted our study area, both pre- and post-hurricane Ike. The Atlantic basin dataset of historical

Table 2 Adjusted (to 2014) property damage and fatality estimates per year across 60 counties for the following hazards: flooding, hail, thunderstorms, hurricanes, storms, hurricanes, wind, and tornados

Year	Property damage (adj. 2014)	Property damage per capita (adj. 2014)	Number of fatalities
Pre-Ike			
2003	54,296,475.97	1136.93	1
2004	25,306,564.17	780.18	2
2005	2,746,975,758.13	80,420.09	5
2006	30,068,802.30	515.92	8
2007	39,910,735.98	423.74	15
Ike* and post-Ike			
2008*	4,668,467,462.19	84,238.80	28
2009	77,128,119.94	826.87	10
2010	18,404,319.62	286.78	1
2011	7,108,531.45	265.90	3
2012	18,471,767.62	337.61	4

* Ike made landfall in that year

hurricane tracks (1851–2015), obtained from NOAA Coastal Services Center, is useful for that purpose (see Knapp et al. 2010). We followed the approach used in Esnard et al. (2011), but unlike that study which focused on the formulation of a displacement risk index, here we did not distinguish between hurricane categories 1–5, and we were interested in school districts rather than counties. As outlined in Esnard et al. (2011, p. 849), ArcGIS software functionality was used to intersect the storm tracks (line) with the school district boundary shapefile. A new shapefile was derived with attributes including the geographic relationship between storm tracks and school districts. The ArcMap summarize function was then used to aggregate the storm information at the school district level. The return periods and probability were then calculated as follows:

Return Period (RP) = 165 year period of record (years 1851–2015)/number of storm/ hurricane strikes
Probability = 1/RP

3.4.3 Additional exposure variables

A hurricane is a large circulating system (rotating counterclockwise in the northern hemisphere) of thunderstorms, with an organized wind field, within which wind speed declines with distance from the center of the storm. Hurricanes form and sustain themselves with the energy from warm humid air over large bodies of water, such as the Atlantic Ocean or the Gulf of Mexico. The intensity of a hurricane decreases quickly once the hurricane moves over land, where friction increases and that energy is not available. Therefore, there are three other exposure variables that we utilize in addition to the return period: (1) right side of the storm track, (2) coastal/non-coastal location, and (3) percent of school district classified as urban.

Right side of storm track: in the northern hemisphere, the counterclockwise circulation of hurricanes produces stronger wind speeds on the right side versus the left side of the storm, due to the force produced by the motion of the entire system. As a hurricane hits the coast, the wind speeds from the cyclone on the right side of the storm will be intensified by the forward speed of the hurricane. A 25 miles per hour (mph) forward speed would result in an increase in the hurricane-induced sustained wind speed by 25 mph on the right side. Conversely, the wind speed on the left side will be blowing in the opposite direction and therefore decrease by an amount corresponding to the speed of the system. A difference in wind speed between the left and right side of 50 mph is possible. In addition, the right side of the storm typically contains more intense rainfall and storm surge. Counterclockwise winds push the storm surge toward the coast and inland on the right side of the storm.

Coastal/non-coastal: compared to inland counties, coastal counties are exposed to storm surge, in addition to wind and rain. The coastal/non-coastal school district designation is based on a district centroid residing within a coastal county, as designated by NOAA.[3]

Percent of school district classified as urban: The fourth exposure variable utilized in this study is the percent of the geographic area of the school district classified as urban. We use the U.S. Census binary urban/non-urban area designations to capture the differential effects that a hurricane may have in built up versus less built up areas.

4 Methods and results

In order to assess how school closures are distributed and potentially related to physical exposure and school demographic factors, we use two main methods, discussed in more detail below. The first is measurement of the spatial autocorrelation of school district closure days and identification of cluster concentrations relative to the Hurricane Ike's wind swath impact area. Second is the measurement of the relationship between school closure and vulnerability factors.

The nine variables (four demographic, one socioeconomic, and four exposure) used in the analysis are described in Table 3. Both spatial and non-spatial data had to be pre-processed. All mapping and spatial analysis was conducted using ESRI ArcGIS 10.4®. GIS shapefile data were collected from a variety of sources, including Texas Education Agency (TEA), the Houston–Galveston Area Council, National Oceanic and Atmospheric Administration (NOAA), National Center for Education Statistics (NCES), and the US Census. The spatial data, primarily in the geographic coordinate system (GCS), were reprojected to NAD 1983 Texas Statewide Mapping System (meters).

4.1 Measuring spatial autocorrelation and mapping cluster concentrations

As a first step, we wanted to understand the spatial distribution of school closings, relative to the location of the storm track. Identifying significant spatial patterns within the data through Global Moran's I inferential statistics allows for the exploratory generation of alternative hypotheses to account for the probability that school district closures are not

[3] NOAA's list of coastal cities and counties. Retrieved from: https://www.census.gov/geo/landview/lv6help/coastal_cty.pdf.

Table 3 Data and variables

Variable	Description/justification	Data source
Socioeconomic and demographic vulnerability (school district)		
% Economically disadvantaged	Indicator of socioeconomic vulnerability. Calculated as the sum of the students coded as eligible for free or reduced-price lunch or eligible for other public assistance (examples of "other public assistance" include the following: programs under Title II of the Job Training Partnership Act (JTPA); food stamp benefits; or Supplemental Nutrition Assistance Program (SNAP); Temporary Assistance to Needy Families (TANF); and Pell grant or comparable state program of need-based financial assistance), divided by the total number of students at the school district level	Texas Education Agency (TEA)
% Black, not of Hispanic origin; % Hispanic; % White, not of Hispanic origin; % Other (includes % American Indian or Alaska, and %Asian or Pacific Islander	Indicators of socioeconomic vulnerability. Ethnicity categories are coded for school administration purposes	Texas Education Agency (TEA)
Physical vulnerability–exposure		
% Classified as urban	Captures the differential effects that a hurricane may have in built up versus less built up areas operationalized as the % of the school district area that is classified as urban	U.S. Census Bureau
Left and right side of Ike	There is a difference in wind intensity and direction on the two sides of the hurricane track. The area on the right side face stronger and more extensive winds and higher storm surge compared to the left side of the hurricane track (Kim et al. 2016, p. 413)	Authors—generated using ArcMap 10.4
Binary coastal/non-coastal	Coastal counties are more exposed to storm surge, in addition to wind and rain	U.S. Census Bureau
Hurricane Probability	Hurricane return periods are a suitable proxy for repeated exposure in our large study area. This is based on historical hurricane tracks that crossed the counties in which the school districts are located	Calculated by authors—see Section 3.2.2

spatially randomly distributed based on a z-distribution (Moran 1950).[4] The null hypothesis of a random spatial distribution of school district closures was rejected, and there is a high probability that statistically significant clustering existed.

In addition to identifying an overall understanding of spatial patterns within the dataset, we identified the within study area locations and intensity of spatial patterns through the Getis–Ord Gi* statistic, more commonly known as hot spot analysis (Getis and Ord 1992). This additional exploratory cluster analysis allows us to determine where closures are concentrated outside of the expected coastal counties, and to what extent the school district closure days were observed based on a *z*-distribution. The hot spot analysis of school district closure days utilizes the same special weight matrix generated for Global Moran's I.

Identified clusters are groupings of school districts with similarly high closure days significant at the $p \leq 0.05$ level. Clusters of elevated school district closure days were located where the Ike path made landfall, and predominantly to the right of the storm track (Fig. 6), consistent with our expectations. Six counties (Chambers, Liberty, Jefferson, Hardin, Orange, and Galveston) had 100% of the school districts exhibiting statistically significant clustering of a higher number of closed school days. There are no statistically significant ($p \leq 0.05$) lower-than-expected school district closure days in the study area.

4.2 Measuring the relationship between school closure and vulnerability factors

For this part of the analysis, we are interested in understanding the relationship between the number of days a school district is closed and the track of Hurricane Ike, controlled by several vulnerability factors. Although in some circumstances the linear form of GLM may provide reasonable results, count data are better modeled with a Poisson or negative binomial distribution model, or their respective zero-inflated forms, the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) (Long and Freese 2006; Guikema and Quiring 2012).

The dependent variable (DV), number of days that a school district has been closed as a result of Hurricane Ike, has a range of integer values between 0 and 19. The distribution was heavily skewed toward zero with 112/294 (38% of total) instances of zero school closure days. Therefore, a Poisson or negative binomial model was more appropriate than a linear model.

The tendency is for the Poisson distribution to predict less dispersion in the outcome than actually exists in the data (Long and Freese 2006). The classical solution has been to use the negative binomial distribution within the GLM framework (Zeileis et al. 2008), or the zero-inflated forms. To test for overdispersion, we fitted a GLM

[4] To measure the degree to which school district closure days were spatially correlated, we used a weighted distance of *k*-nearest neighbor. Through a spatial weight matrix, we set *k* as 3 nearest schools districts for a district under observation. The decision to use a spatial weighted matrix of *k*-nearest neighbor was due to the heavily skewed nature of school closure days within the study area. The district school closure days variable has a high degree of right skewness (1.11, SE = 0.14) and a kurtosis of 0.50 (SE = 0.28). The median number of school district closure days was 2, with an interquartile range of 6 days. A negative clustering statistic would indicate a significantly ($p < 0.05$) dispersed spatial pattern of school district closures. A positive statistic would indicate underlying clustering of school district closures. Where no pattern exists with school district closures, the Global Moran's *I* would yield an insignificant statistic. The Global Moran's I was significantly positive at 0.72 (*z*-score = 16.21; $p < 0.001$) under the spatial weighted matrix using *k*-nearest neighbor.

with a quasi-Poisson distribution to check the dispersion parameter.[5] The output showed a dispersion parameter of about 2.7, indicating the presence of overdispersion. Therefore, the negative binomial distribution is more appropriate. The Vuong test indicated that a ZINB regression fits the data better than a GLM.[6]

The results of the ZINB model are presented in Table 4 in the form of four models, each with a different set of independent variables. The ZINB model assumes two processes; a count model and a model to explain the zero outcomes. In the present case, the zero counts are explained by location relative to the coast and right side of the Ike track. The association is significant at the 0.001 level for both variables. The log-likelihood χ^2 test versus the null model is also significant at the 0.001 level, indicating the model fits the data better than a model with no predictor variables. The coefficients are log-odds and indicate the direction of the association, but not the magnitude. Model I regresses only the demographic variables and Model II only the physical exposure variables. Model III combines both sets, and Model IV adds Coastal District * Right Side of Storm Track as an interaction term.

The results are consistent across model specifications and indicate that higher probabilities of hurricane strikes (i.e., shorter hurricane return periods), more urbanized school districts, and school districts located in coastal counties on the right side of Ike's path, have significant positive associations with an increase in the number of school closure days. As expected, shorter hurricane return periods are concentrated in the coastal counties of Brazoria and Harris (probability = 0.28), west of where Hurricane Ike made landfall (Fig. 5). None of the demographic characteristics had a significant association with the number of days closed except the coefficient on percent Hispanic, indicating that an increase in the percentage of the Hispanic population is associated with a decrease in the number of days closed, relative to the White population.

In Model IV, the coefficients on the dummy (i.e., right and coastal) variables change as a result of the addition of the interaction term, but the significance on any other terms remains the same. The interaction term indicates that coastal districts on the right of the storm are associated with higher number of school closure days than other districts. There is no significant difference between districts on the right and left side in non-coastal districts, holding the other factors constant. The difference between coastal and non-coastal districts is significant and negative, indicating that on the left side of the track coastal districts have fewer closure days than non-coastal districts, holding the other variables constant.

5 Discussion and conclusions

This paper focuses on an under-examined social institution (schools), an important predictor of student success, in the context of a major hazard threat for a large proportion of the USA (i.e., hurricanes). These types of assessments and analyses are important given their lasting impact on society. Higher levels of vulnerability (as related to location,

[5] Overdispersion was tested using dispersiontest() in the 'AES' package, as well as glm.nb with a quasi-Poisson distribution, in RStudio 1.0.136.

[6] The Vuong test is a commonly used method to determine whether a ZINB regression better fits the data than a GLM with a negative binomial distribution (Long and Freese 2006). The Vuong test indicates a p value < 0.05, rejecting the null hypothesis that zero-inflated Poisson regression is most appropriate. However, Wilson (2015) warns that Vuong may not be the appropriate test because of an error in the non-nested model assumption. The results are similar across four model distribution specifications (i.e., Poisson, negative binomial, ZIP, ZINB).

Table 4 Zero-inflated negative binomial

	Model I	Model II	Model III	Model IV
DV = count of days closed				
% Black[a]	0.003		− 0.003	− 0.002
	(0.005)		(0.004)	(0.003)
% Hispanic	− 0.001		− 0.01***	− 0.01***
	(0.004)		(0.004)	(0.004)
% Other	0.03		− 0.004	− 0.001
	(0.02)		(0.01)	(0.01)
% Econ dis	− 0.01*		0.003	0.003
	(0.005)		(0.004)	(0.004)
Urban share		0.2	0.5*	0.5**
		(0.2)	(0.2)	(0.2)
Probability		6.4***	7.1***	7.2***
		(0.9)	(0.9)	(0.9)
Right side		0.8***	0.6***	0.1
		(0.1)	(0.1)	(0.1)
Coastal district		0.2**	0.3**	− 0.4**
		(0.1)	(0.1)	(0.2)
Coastal * right				1.0***
				(0.2)
Constant	2.0***	0.2	0.3	0.6***
	(0.2)	(0.2)	(0.2)	(0.2)
N	294	294	294	294
Log likelihood	− 651.5	− 600.9	− 592.3	− 579.2

Standard errors in parentheses

[a]White is the race reference group

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

exposure, and demographic factors) increase the likelihood that schools will close in the aftermath of disasters. In turn, this may relate to slower recovery. This expands our understanding of how schools in this sixty-county study area may be affected by a hurricane disaster.

The choices of study area and unit of analysis depend on one's disciplinary focus, research project, as well as data availability. As defined by Lewis-Beck et al. (2011), a unit of analysis is the most basic element of a scientific research project; the subject (who or what) of study about which an analyst may generalize. We use school districts, but units of analysis can range from an individual (e.g., such as in child trauma studies) to hazard zones (e.g., flood hazard zones) to census tracts.

Typical study areas used for hurricane damage and vulnerability assessments include the communities or counties impacted by the disaster, or a comparison between coastal and non-coastal areas. We used hurricane Ike's wind swath as our study area, which captured as many as sixty counties and enabled examination of impacts in coastal and non-coastal (far inland) counties, as well as urban and rural areas. As previously noted, the wind swath provides a good approximation of the region impacted by Hurricane Ike, which had a large wind field that covered a broad area of southeast Texas.

It is not surprising that school districts in our sixty-county study area exhibited a wide range of closure days (0–19) after Hurricane Ike. We can speculate at this point that some schools closed as a preparedness measure, but reopened quickly depending on access and damage. Others closed for longer periods, needing repairs to school facilities and other

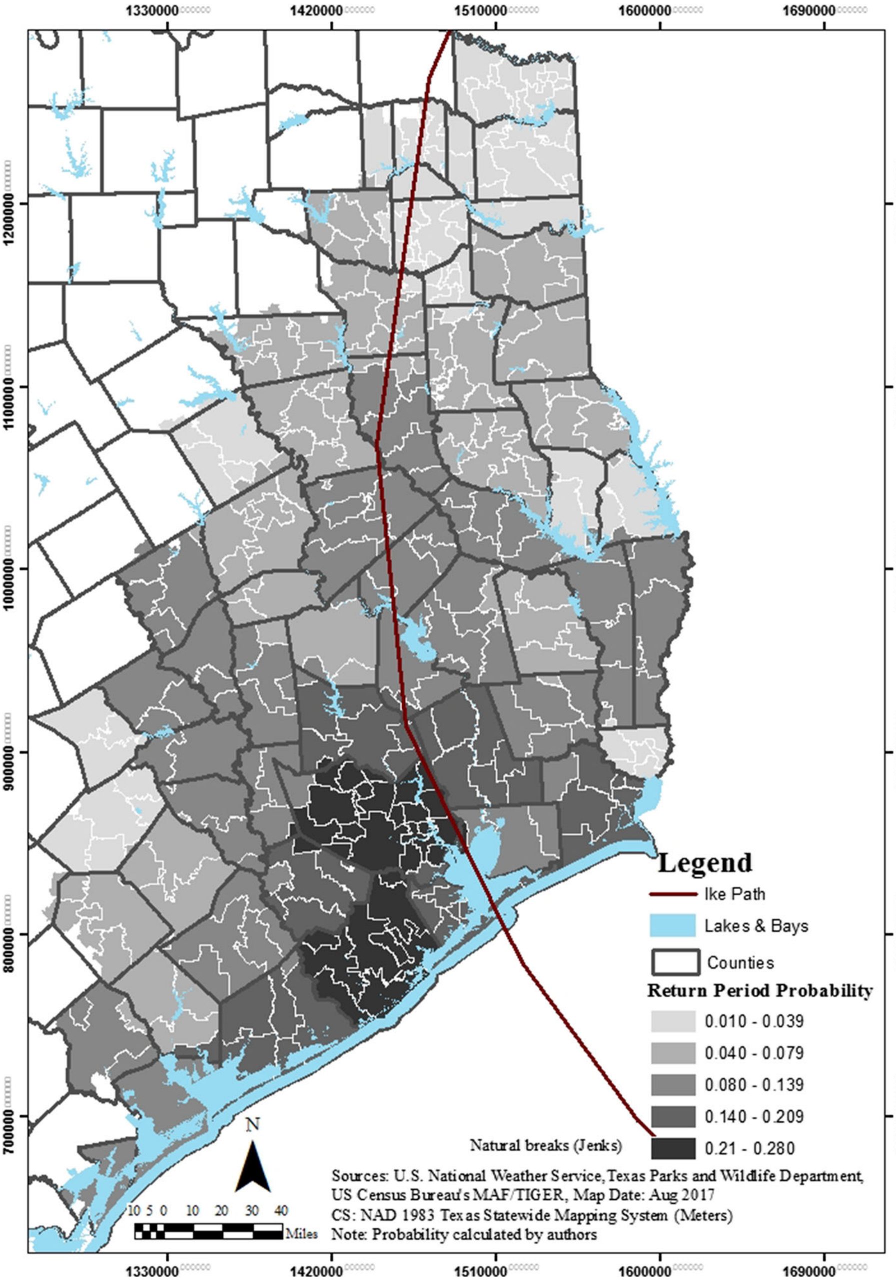

Fig. 5 Probability of return periods by school district

community infrastructure. The year following Ike (2009) proved to be the third costliest year in terms of property damage and lives lost within the study area. However, all recovery was managed locally, as the disaster did not rise to the level of a FEMA disaster declaration. This highlights the need to understand the potential compounding effects of

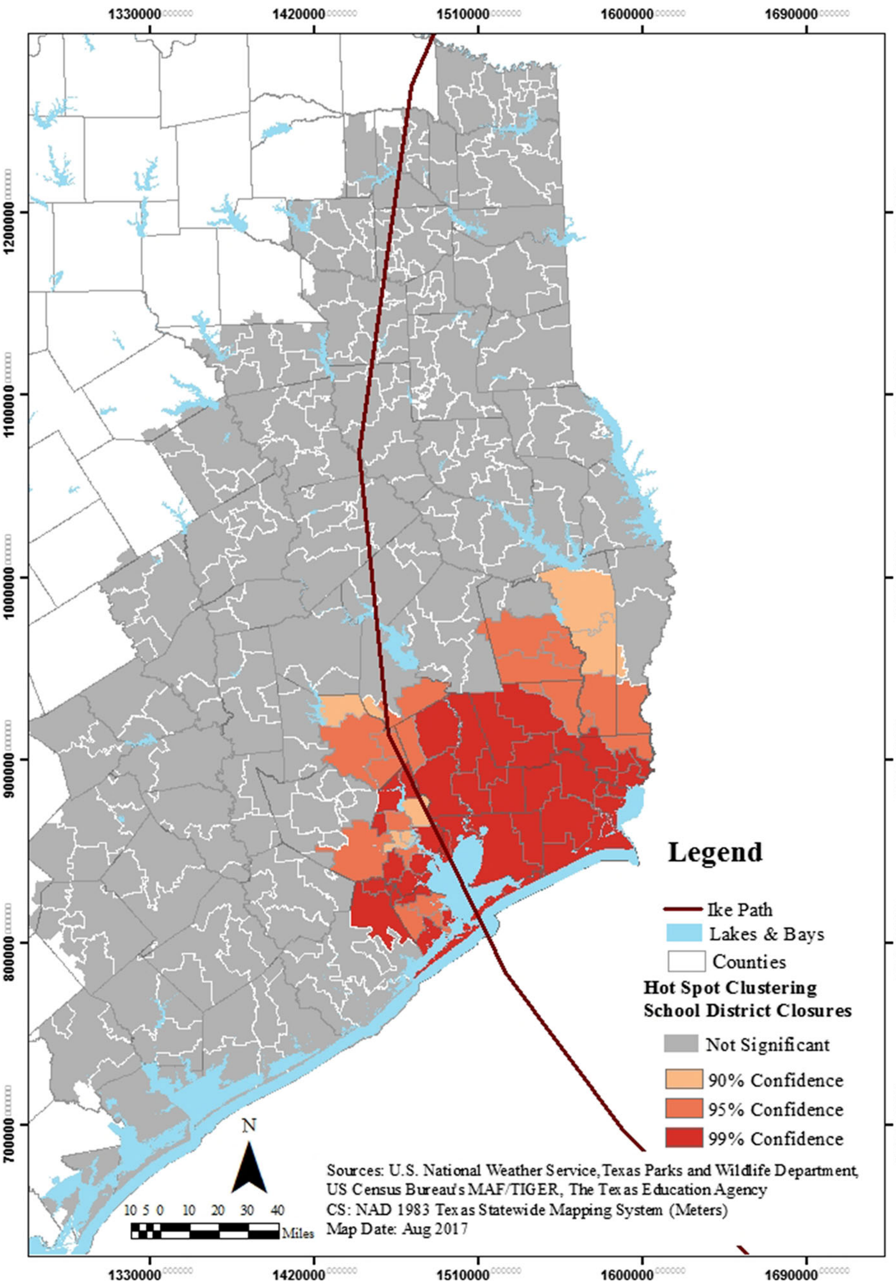

Fig. 6 Exploratory analysis map: Local spatial clustering of school district closures using Getis–Ord Gi* Hotspot analysis. Statistical significance was determined using 95 and 99% confidence intervals

repeat disaster exposure; for some schools, it may lengthen recovery, while for others a disaster may have increased resiliency through capacity building and preparedness over time.

The combination of spatial and statistical methods—exploratory cluster analysis and zero-inflated negative binomial regression models—advances interdisciplinary research frameworks and methods which are important for addressing the complex nature of community and school vulnerability. For this analysis, data on demographics and socioeconomic status were captured at the school district level (e.g., percentage of children who are economically disadvantaged, percentage of minority students) to test how socioeconomic and demographic vulnerability may differentially influence the pattern of school closures. As previously noted, we found that an increase in the percentage of Hispanics students versus White students is associated with a decrease in the number of school days closed. This finding is not supported by the social vulnerability literature, which traditionally includes Hispanics in the vulnerable population category (Cutter et al. 2003, 2010; Laska and Morrow 2006; Peacock 2010; Esnard et al. 2011). While we were first surprised by that finding, a possible partial explanation specific to Hurricane Ike's path and wind swath emerges when Fig. 2 (spatial patterns of school closures) and Fig. 4 (spatial pattern of Hispanic children in school districts) are compared. We see a concentration of Hispanics on the left side of hurricane Ike track which has less school closure days. This finding reinforces the need to understand that the area on the right side face stronger and more extensive winds and higher storm surge compared to the left side of the hurricane track (Kim et al. 2016, p. 413). This type of study also makes the case for the importance of comprehensive datasets on school closures, demographic data, and hurricane tracks to allow for coupling of physical exposure and socioeconomic vulnerability data.

We acknowledge several limitations of our study. First, a limited subset of socioeconomic vulnerability variables was used in this study. A future study can combine socioeconomic data at multiple units of analysis (e.g., school, school district, census block group) to: (1) examine the variation, if any, between school/school district and community with which the schools are located and (2) to assesses whether the variation is predictive of school closure.

Second, it is not clear that vulnerable students (e.g., due to risk factors such as ethnic/racial minority status, low socioeconomic status, lower performance scores) attend schools that, as an institution, are vulnerable to disasters. Given that we were using administrative data, we did not have access to individual child information. It will be important for future studies, when longitudinal data become available, to test the extent to which vulnerable students are connected with vulnerable schools in the context of disasters. Initial work in this area provides evidence that these issues are interconnected, and the relationships are bidirectional. As mentioned earlier, many children displaced by Hurricanes Katrina and Rita were relocated into higher performing schools. These displaced students performed better over time (Fothergill and Peek 2015; Hango 2006; Pane et al. 2008; Sacerdote 2008). Schools affected by disasters may also differentially impact children who are already vulnerable. The majority of this work to date has been based on case studies (e.g., Fothergill and Peek 2015). Thus, future studies are needed that will examine these issues longitudinally.

Third, there is also the need to account for resources and capacity of the affected school districts and their communities, which was beyond the scope of this study. Institutional context, past experience, and community resilience are important factors that can affect the duration of school closures. Various foundational studies (Robinson et al. 2014; Robinson 2011, 2012) document collaboration (impetus and strategies) between school districts, a broader network of partners from geographically proximate local emergency management agencies, and other public and non-profit sectors (e.g., religious institutions, welfare agencies, business organizations, housing organizations, transportation agencies) that have core missions other than emergency management. We do not account for declines in institutional infrastructure or community resilience factors, which have differential impacts on school district closures. In-depth interviews with school district principals and superintendents would reveal important details about Ike's impact on individual schools, and administrative records at the school level, such as emergency planning measures, implemented hazard mitigation efforts, and recorded past damage from other storms, would be valuable additional control data. Such insight on community capacity, partnerships, and collaboration, while important, is best captured closer in time to a disaster event. Such rich data are beyond our reach a decade after the event.

Fourth, further research is needed to examine linkages at multiple scales—school (structural integrity and student demographics), school district and school attendance zones (administrative and institutional plans, policies, and budgets), and neighborhood/community county (socioeconomic profile and recovery timeframe of interdependent community components—e.g., homes, businesses, critical infrastructure).

Understanding the pre-disposition of schools and other critical facilities to hazards and extreme events is important for developing appropriate mitigation and adaptation strategies that are forward-looking; strategies and planning that acknowledges increases in the severity of precipitation and storms. Findings presented here are an important indication that lessons learned from Hurricane Ike and school closures may present a useful case study toward understanding how to prepare for future disasters.

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