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How community vulnerability factors jointly affect multiple health outcomes after catastrophic storms

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ABSTRACT

Background: While previous studies uncovered individual vulnerabilities to health risks during catastrophic storms, few evaluated the population vulnerability which is more important for identifying areas in greatest need of intervention.

Objectives: We assessed the association between community factors and multiple health outcomes, and developed a community vulnerability index.

Methods: We retained emergency department visits for several health conditions from the 2005–2014 New York Statewide Planning and Research Cooperative System. We developed distributed lag nonlinear models at each spatial cluster across eight counties in downstate New York to evaluate the health risk associated with Superstorm Sandy (10/28/2012–11/9/2012) compared to the same period in other years, then defined census tracts in clusters with an elevated risk as “risk-elevated communities”, and all others as “unelevated”. We used machine-learning techniques to regress the risk elevation status against community factors to determine the contribution of each factor on population vulnerability, and developed a community vulnerability index (CVI).

Results: Overall, community factors had positive contributions to increased community vulnerabilities to Sandy-related substance abuse (91.35%), injuries (70.51%), cardiovascular diseases (8.01%), and mental disorders (2.71%) but reversely contributed to respiratory diseases (−34.73%). The contribution of low per capita income (max: 22.08%), the percentage of residents living in group quarters (max: 31.39%), the percentage of areas prone to flooding (max: 38.45%), and the percentage of green coverage (max: 29.73%) tended to be larger than other factors. The CVI based on these factors achieved an accuracy of 0.73–0.90 across outcomes.

Conclusions: Our findings suggested that substance abuse was the most sensitive disease susceptible to less optimal community indicators, whereas respiratory diseases were higher in communities with better social environment. The percentage of residents in group quarters and areas prone to flooding were among dominant predictors for community vulnerabilities. The CVI based on these factors has an appropriate predictive performance.

Abbreviations: CVI, community vulnerability index; BRT, boosted regression tree; LVC, low vulnerability communities; HVC, high vulnerability communities

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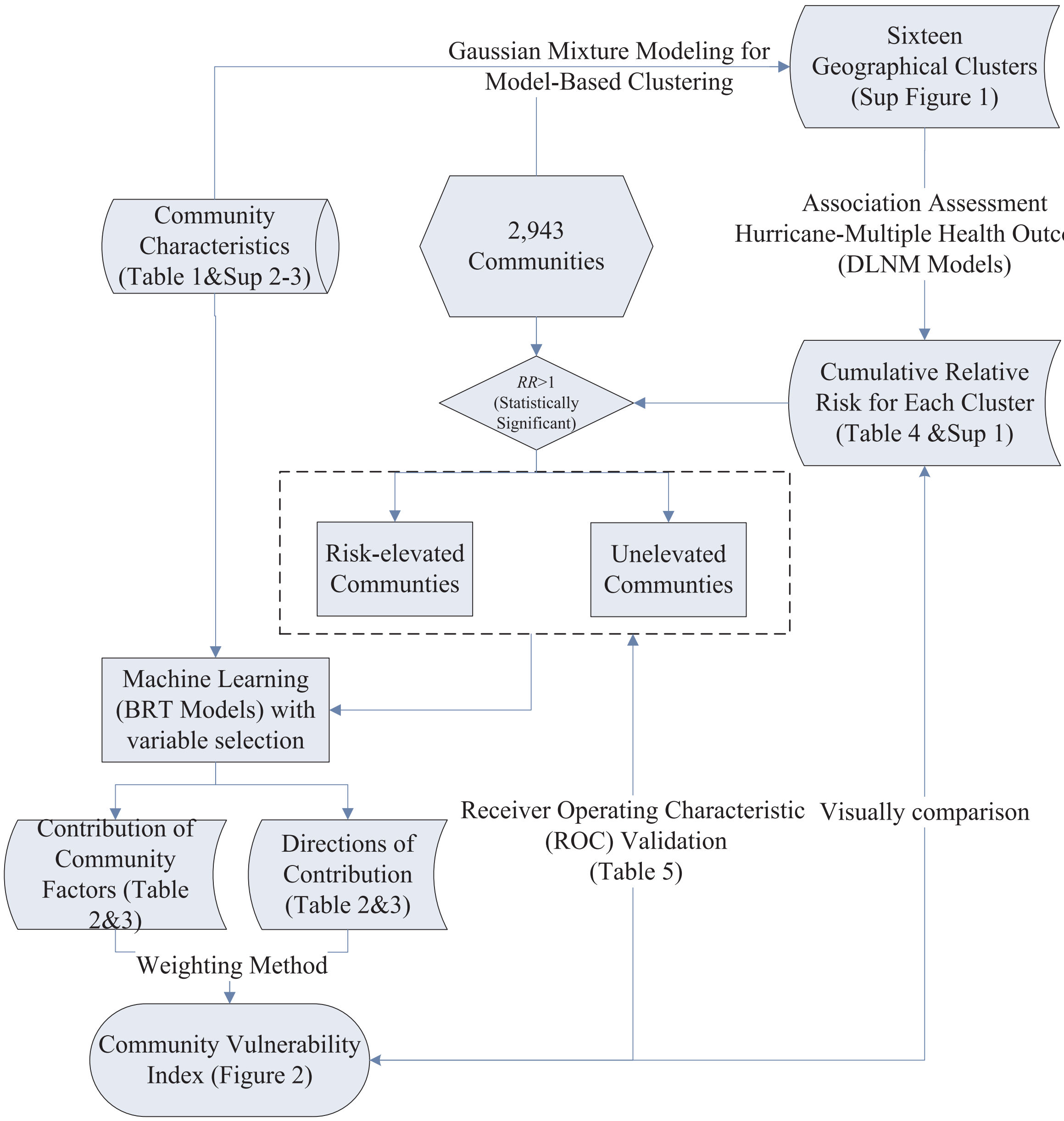

Fig. 1. Procedure for developing a community vulnerability index: major steps include spatial clustering, storm-health association assessment, contribution evaluation and index development.

1. Introduction

Over the past decade, there has been an increase in hurricanes and superstorms across North America as a potential result of climate change. Health risks associated with residents in areas prone to those catastrophic storms are a major concern, and has become an emerging research area (Brackbill et al., 2014; Eisenman et al., 2007; Shultz and Galea, 2017; Sifferlin and Vick, 2017). Growing efforts are being made towards identifying vulnerable groups for emergency preparedness and response (Ali et al., 2017; Milch et al., 2018; Zoraster, 2010). Among existing studies, majority evaluated individual vulnerability variations (Ali et al., 2017; Messias and Lacy, 2007; Mills et al., 2007; Santos-Burgoa et al., 2018; Simms et al., 2013). For instance, Santos-Burgoa et al. (2018) investigated the mortality among Puerto Rico residents following Hurricane Maria using mortality data stratified by individual information including age, sex, and residential municipality of each death. Their findings identified individuals at greatest risks were males, ages ≥65 years and those of low socioeconomic status. Mills et al. (2007) suggested higher risk of acute stress disorders after Hurricane Katrina among individuals who were female, black, injured or with increased perception of life-threat during the event. Understanding the individual vulnerability is important, however, evaluating the community vulnerability and identifying spatial hotspots at the highest health risk are of greater public health importance for policy makers and practitioners to target limited funds to maximize the health benefit.

Among limited studies evaluating community vulnerability, several were descriptive studies that compared the difference in few socio-demographic characteristics of the affected population from different areas (Brunkard et al., 2008; Logan, 2006; Pastor et al., 2006; Zoraster, 2010). Additionally, comprehensive analytical studies generally developed an index based on multiple factors to represent population vulnerability to environmental hazards, such as catastrophic storms. Examples of these indices include the social vulnerability index by the Agency for Toxic Substances and Disease Registry of the U.S. Centers for Disease Control and Prevention (Barry et al., 2011a; Cutter et al., 2003) and other similar indices, including heat vulnerability index developed following similar procedures (Bathi and Das, 2016; Emrich, 2015; Nayak et al., 2018; Rygel et al., 2006). However, these existing indices often suffer from multiple limitations. For instance, the direction (+/−) of the impact of community factors on population vulnerability is often not evaluated (i.e. factors representing lower socioeconomic status are automatically assumed to be associated with higher population vulnerability). Also, the weight of each factor is not considered and all community factors are assumed to have an equal contribution to population vulnerability. Finally, the existing indices have not considered specific health outcomes or specific exposure events involved in evaluating population vulnerability (Bjarnadottir et al., 2011; Wolkin et al., 2015). Therefore, a new index that considers the weight and direction (+/−) of each community factor, as well as considering major exposure and health outcomes categories are necessary for an accurate prediction of population vulnerability.

To address the knowledge gaps described above, we proposed a new multi-stage procedure to: (1) identify community characteristics that contribute to increased vulnerability; (2) develop a novel community vulnerability index by weighting selected community factors with their contributions (i.e. weights with directions) to the vulnerability; (3) evaluate the vulnerability of affected New York State (NYS) residents by multiple health outcomes (cardiovascular diseases, respiratory diseases, intestinal infectious diseases, mental disorders and injuries) during Superstorm Sandy, one of the most destructive storms in U.S. history (Diakakis et al., 2015; Hurricane Research Division, 2014); and (4) map the resulting community vulnerability index to health hazards in NYS, which can be used by government agencies to optimize resource allocations.

2. Materials and methods

2.1. Study procedures and areas

To overcome major limitations of existing population indices described above, we developed a new community vulnerability index combining the advantage of distributed lag nonlinear models (i.e. fully capturing the health effects of Superstorm Sandy during and after storm period) with the advantage of machine-learning techniques (i.e. ruling out the potential collinearity and outlier issues in the data). We proposed the following multi-stage procedures (Fig. 1):

Stage 1. Spatial Clustering: this study covers 2943 census tracts (referred to as "community" from here on) in eight NYS counties affected by Superstorm Sandy from October 28, 2012 to November 9, 2012 (Bronx, Kings, Nassau, New York, Queens, Richmond, Suffolk, and Westchester counties). We grouped census tracts into spatial clusters based on the similarity of community characteristics as listed in Table 1.

Stage 2. Association Assessment: Distributed lag nonlinear models in each spatial cluster to determine the storm-health associations from 2005 to 2014, controlling for time-varying confounders such as weather and air pollution indicators.

Stage 3. Contribution Evaluation: Determine risk-elevated and unelevated status for each community based on the previous step, and evaluate the contribution (weight with direction) of each community factor using boosted regression tree models

Stage 4. Index Development and Validation: Develop a new community vulnerability index, validate and map the index.

2.2. Outcome definitions

Health data were obtained from the New York State Department of Health Statewide Planning and Research Cooperative System (SPARCS) which is a legislatively mandated database with coverage for over 95% of hospital records in NYS (Lin et al., 2012, 2008; Zhang et al., 2018). The outcome for storm-health association assessment at cluster-level was the daily number of emergency department visits for each health outcome between 2005 and 2014. We focused on multiple disease groupings including cardiovascular diseases (the International Classification of Diseases, Ninth Revision (ICD 9) code: 393–396, 401–405, 410–415, 427, 428, 430–434, 436–438; resulting in a total of 420,982 cases), respiratory diseases (ICD 9 code: 491–496, 518; 1,054,241 cases), intestinal infectious diseases (ICD 9 code: 001–009; 89,275 cases), injuries (ICD 9 code: E880-E910; 2,516,619 cases) and mental disorders (ICD 9 code: 290–300, 303–305; 1,411,657 cases). We included these health outcomes since they were major disease groupings which were previously reported to be associated with catastrophic storms, and their associations were biologically plausible (Becquart et al., 2018; Currie and Rossin-Slater, 2013; Lauper et al., 2017; Lin et al., 2016; Rath et al., 2011). Additionally, we also included substance abuse (ICD 9 code: 303–305; 735,579 cases) which has been identified as an important mental disorder during storms as suggested in prior studies (Pouget et al., 2015; Rohrbach et al., 2009). All residential addresses for cases were geocoded and assigned to spatial clusters by matching their coordinates with the boundary of areas.

The outcome for the evaluation of contributions (weight with direction) of community factors was health risk elevated and unelevated status in each community. We defined census tracts located in clusters with significantly elevated health risk detected in the association assessment as risk-elevated communities, otherwise as risk-unelevated communities.

2.3. Exposure assessment

The exposure for the association assessment using distributed lag nonlinear models was a date indicator showing the storm period, reference period, and all others. As the emergency declaration and evacuation order were issued in advance of Sandy's landfall on October 28, 2012, and the US Federal Emergency Management Agency (FEMA) emergency incident period ended on November 9, 2012, we defined both dates as the exposure beginning and ending period (Bloom et al., 2016; Lin et al., 2016). To control for the confounding of seasonality and long-term trends, we defined the period of October 28 to November 9 in other years as the reference period. Additionally, in order to evaluate the impact of Sandy over the longer term, we then conducted a year-round comparison by extending the exposure period to the first and second year following Sandy (excluding the Sandy period), with other years as the reference period.

The exposure for the contribution evaluation of community factors included variables from four domains: (1) *the Socioeconomic Status Factors* including Below Poverty (%), Unemployed (%), Per Capita Income (USD), and No High School Diploma (%); (2) *the Household Composition and Disability Factors* including Ages ≥ 65 years (%), Ages ≤ 17 years (%), Disabled (%), and Single-Parent Households (%); (3) *the Minority Status and Language Factors* including Minority (%) and Speak English "Less than Well" (%); (4) *the Housing and Transportation Factors* including Multi-Unit Structures (%), Mobile Home (%), Crowding (household with more people than rooms, %), No Vehicle (household without vehicles, %), and Group Quarters (persons in institutionalized group quarters, %). Each community factor was dichotomized at the 90th percentiles as adopted from previous studies (Barry et al., 2011a; Chau et al., 2014). Pairwise correlations were checked in the preliminary study to confirm that these factors were not highly correlated ($\rho \leq 0.75$). We included three additional landscape indicators: (1) *the percentage of areas prone to flooding* which represented the combined effects of community landscape factors such as elevation, land use, and green infrastructure; (2) *the percentage of developed areas* (defined as areas with construction materials and daily human activities); and (3) *the percentage of green coverage* (defined as areas covered by forest and shrub land). We also included a random term for determining the significance of community factors. We included these factors since they were considered to be the most important and comprehensive predictors for residential environment and population

Table 1
Community characteristics by area.

Factors	Areas*	Percentiles Minimum	25th	50th	75th	Maximum
Below poverty (%)	Risk-elevated	0.0	5.3	10.2	20.1	62.9
	Unelevated	0.0	6.1	12.8	23.7	100.0
Unemployed (%)	Risk-elevated	0.0	5.0	7.2	10.0	46.9
	Unelevated	0.0	6.2	8.8	12.5	100.0
Per capita income (USD)	Risk-elevated	8364.0	25513.0	38630.0	58692.5	198534.0
	Unelevated	622.0	19577.8	27512.5	38029.2	247852.0
No high school diploma (%)	Risk-elevated	0.0	4.3	9.9	18.9	55.9
	Unelevated	0.0	8.0	15.1	25.9	76.7
Aged ≥65 (%)	Risk-elevated	0.0	9.2	13.3	17.7	43.7
	Unelevated	0.0	9.2	12.5	16.2	100.0
Aged ≤17 (%)	Risk-elevated	0.0	14.2	19.6	23.9	62.4
	Unelevated	0.0	18.4	22.1	25.8	55.7
Disabled (%)	Risk-elevated	0.0	6.7	9.0	12.2	34.9
	Unelevated	0.0	7.1	9.1	11.7	98.2
Single-parent households (%)	Risk-elevated	0.0	2.7	5.3	11.3	37.6
	Unelevated	0.0	3.9	7.9	15.2	57.1
Minority (%)	Risk-elevated	0.0	19.2	35.7	69.6	100.0
	Unelevated	0.0	28.0	63.2	94.2	100.0
Speak English less than well (%)	Risk-elevated	0.0	1.4	5.1	10.5	51.6
	Unelevated	0.0	2.5	6.9	15.9	60.0
Multi-unit structures (%)	Risk-elevated	0.0	5.2	31.1	84.9	100.0
	Unelevated	0.0	1.8	17.1	59.5	100.0
Mobile home (%)	Risk-elevated	0.0	0.0	0.0	0.0	5.8
	Unelevated	0.0	0.0	0.0	0.0	34.1
Crowding (%)	Risk-elevated	0.0	1.6	4.0	8.0	52.2
	Unelevated	0.0	1.9	5.7	12.0	47.1
No vehicle (%)	Risk-elevated	0.0	10.8	42.2	70.1	93.1
	Unelevated	0.0	10.1	34.9	61.9	97.7
Group quarters (%)	Risk-elevated	0.0	0.0	0.4	3.8	49.0
	Unelevated	0.0	0.0	0.2	0.8	100.0
Area prone to flooding (%)	Risk-elevated	0.0	0.1	0.4	0.8	1.0
	Unelevated	0.0	0.0	0.0	0.0	1.0
Developed areas (%)	Risk-elevated	0.0	0.6	0.7	0.8	1.0
	Unelevated	0.0	0.7	0.8	0.9	1.0
Green coverage (%)	Risk-elevated	0.0	0.0	0.0	0.0	0.3
	Unelevated	0.0	0.0	0.0	0.0	0.6

* Risk-elevated communities: identified with elevated health risk with cardiovascular diseases as an example. Unelevated communities: no elevated risk was detected.

vulnerability (Barry et al., 2011a; Emrich, 2015; Nayak et al., 2018). The community characteristics data were obtained from the American Community Survey (ACS) (Barry et al., 2011a). Additional landscape information was retrieved from previous studies (Forbes et al., 2014; Zachry et al., 2015) and the U.S. National Land Cover Database (Homer et al., 2015).

2.4. Statistical analyses

Stage 1: Spatial Clustering Based on the hypothesis that communities of similar characteristics would respond similarly to external stressors, we grouped 2943 census tracts into 16 clusters with Gaussian finite mixture models fitted by expectation–maximization algorithm in the *mclust* package in R. We estimated the Bayesian Information Criterion (BIC) for models with 1–50 clusters and identified 16 clusters as the optimal number of clusters (Fig. 1, Supplemental Fig. 1) (Fraley and Raftery, 2007, 2002; Scrucca et al., 2016). We stratified the clustering analysis by percentage of areas prone to flooding (0% VS > 0%) to further improve the homogeneity of clusters.

Stage 2: Association Assessment We then used distributed lag nonlinear models with quasi-Poisson distribution to assess the storm-health associations in each cluster (Gasparrini et al., 2010):

$$\text{Log (case)} \sim \text{cb (period)} + \text{ns (time)} + \text{ns (temp)} + \text{ns (dewp)} + \text{others}$$

where case was the daily number of cases, following quasi-Poisson distribution; cb(period) was the cross-basis for the exposure period, a categorical variable with 3 degrees of freedom (df) for the 0–7 lag days space (no lag was considered for year-round comparisons); ns(time) was the spline with 5 df per year to fit potential long-term trend and seasonality; ns(temp) and ns(dewp) represented two splines with 3 df to fit the confounding of temperature and dew point obtained from the Integrated Surface Database (ISD) of the U.S. National Oceanic and Atmospheric Administration (NOAA, https://www.ncdc.noaa.gov/isd); other confounders included indicators for holidays and day of the week to remove temporal patterns, and an auto-regression term at the first order for the outcome to improve the model fit (Bhaskaran et al., 2013; Xiao et al., 2017). Df was determined using the quasi-Akaike's information criterion (QAIC) (Kim et al., 2013; Zhang et al., 2017, 2016a, 2016c). To evaluate the confounding effect of air pollution on the health impact of Sandy, we retrieved the daily ambient concentration of $PM_{2.5}$ (particles less than 2.5 μm in diameter) and 8-hour daily maximum concentration of ozone from the Community Multiscale Air Quality Modeling System of the U.S. Environmental Protection Agency (EPA, https://www.epa.gov/cmaq). We reran the distributed lag nonlinear models with air pollution variables for sensitivity analysis and confirmed that changes in effect estimates of the storm were subtle. From the distributed lag nonlinear model, we obtained short-term (both the lag-specific and cumulative) risk ratio (*RR*) for each health outcome during the exposure period relative to the reference period. For longer-term association assessment (one and two years following the storm period), we followed similar model structures but used generalized additive models instead since no lag was required for year-round comparison.

Stage 3: Contribution Evaluation We then developed Boosted

Regression Tree (BRT) models to regress the risk-elevated and unelevated status against the community factors to evaluate the contribution (weight and its direction) of each factor. The BRT model is a boosted version of traditional regression tree model, which developed hundreds to thousands of trees with each tree built on the residual of the previous one and analogous to a regression term for parametric models (Elith and Leathwick, 2013). If the contribution of each tree, which is reduced by the *learning rate*, is relatively small, then a larger number of trees would be required to capture most of the variance for the data. However, estimates tend be more accurate (Elith et al., 2008). BRT model is based on the recursive binary splits algorithm. Another important parameter is the *tree complex* which determines the depth of interaction between community factors (Elith et al., 2008; Zhang et al., 2016b). In this study, we set the *learning rate* and *tree complex* to 0.001 and 5, respectively, as used in our previous study (Zhang et al., 2016b). For each tree, several "optimal" predictors will be selected according to the *tree complex* parameter and the maximization of homogeneity for each branch of the tree. A *contribution* will then be determined for each predictor according to the number of times it was selected as one of the "optimal" predictors. *Contribution* can also be interpreted as the relative importance (%) of each predictor. The total contribution of predictors is 100%, with predictors having larger contributions considered more important to the outcome. We ran a BRT model within each domain of community factors separately, retained factors with an absolute contribution larger than the random term, and included them into the final model.

Stage 4. Index Development and Validation We weighted each selected factor with its contribution (including the direction of contribution) to population vulnerability as obtained from the BRT model, and summed up these weighted predictors to develop the community vulnerability index:

$$CVI = \sum_{i=1}^{n} Predictor_i * Contribution_i * Direction_i$$

where i represents the 1st to n^{th} predictor used to develop the community vulnerability index. The community vulnerability index was directly comparable across different areas, with larger value representing higher population vulnerability to storm-related health concerns. To display the spatial pattern of the vulnerability index in the map more clearly, we grouped the communities based on the distribution of index into the following categories: (0th, 5th], (5th, 15th], (15th, 25th], (25th, 35th], (35th, 45th], (45th, 55th], (55th, 65th], (65th, 75th], (75th, 85th], (85th, 95th], > 95th percentiles. We mapped the community vulnerability index categories and compared the spatial scenarios of the index with original *RRs*. We defined communities with CVI above the top 15th percentile as high vulnerability communities (HVC) and accordingly, those with CVI on the bottom 15th percentile as low vulnerability communities (LVC). We used the top 15th percentile as the cutoff point for CVI since compared with other cutoff points such as the top 25th and 10th percentiles, the top 15th percentile was the optimal cutoff point yielding the best consistency between the RR and CVI categories. We evaluated the accuracy of the index with the Receiver Operating Characteristics (ROC) curves as used in our previous studies (Jin et al., 2017; Yao et al., 2018, 2017). For sensitivity analysis, we developed another community vulnerability index following the same procedures but with all factors, and also estimated a social vulnerability index, one of the most well-known existing indexes representing the population vulnerability to environmental hazards (Barry et al., 2011a; Cutter et al., 2003). We compared the predictive performance of these indexes by the area under the ROC curve (AUC).

3. Results

3.1. Storm-health associations

The risk of emergency department visits due to cardiovascular diseases, respiratory diseases, mental disorders, injury, and substance abuse significantly increased within the first four days after Superstorm Sandy made landfall. Therefore, we explored the 0–3 day cumulative risk by health outcome in each geographical cluster (Supplemental Fig. 1). We observed increased cumulative risk in 13.42% of tracts for cardiovascular diseases, 26.64% of tracts for respiratory diseases, 11.55% of tracts for mental disorders, 1.26% of tracts for injury, and 7.10% of tracts for substance abuse. We also found increases in the average health risk over longer terms following the storm period. We estimated approximately 3.91% of tracts with elevated risk for mental disorders, and 7.10% of tracts for intestinal infectious diseases and substance abuse within the first year following the Sandy period. We did not observe any increases in health risk for the second year after the event.

For outcomes identified with increased risk, we further investigated the relevant community vulnerability.

3.2. Community factors and contributions

In our descriptive analysis (Table 1) using cardiovascular diseases as the example, there were 395 out of 2,943 census tracts defined as immediately risk-elevated communities based on the Sandy-health association assessment. Across the study area, we observed a large variation for community characteristics. Compared with risk-unelevated communities, we found a higher percentage of multi-unit structures, group quarters, and a higher percentage of areas prone to flooding in risk-elevated communities with a similar pattern for mental disorders. Additionally, in risk-elevated communities we found higher percentages of low-income households for substance abuse and injuries, and lower percentages of minority population for respiratory diseases.

Overall, as presented in Table 2, community factors included in the final machine-learning procedure had positive contribution to increased community vulnerability to Sandy-related risk for substance abuse (overall contribution: 91.35%), injuries (70.51%), cardiovascular diseases (8.01%), and mental disorders (2.71%). In contrast, the overall contribution for respiratory diseases was −34.73%. The relative contribution of community factors varied substantially across health outcomes. Generally, factors in the socioeconomic status domain had larger contributions on injury and substance abuse, while factors in the minority status and language domain, as well as housing and transportation domain had larger contributions on respiratory diseases, cardiovascular diseases and mental disorders. Overall, the contribution of factors in these three domains were greater than those in the household composition and disability domain.

More specifically, (1) for cardiovascular diseases and mental disorders, housing and transportation factors including the percentage of multi-unit structures (contribution: 11.86–12.05%) and group quarters (10.80–12.78%) had the highest contribution among all community factors. The percentage of households without vehicle also contributed to a higher community vulnerability to these two outcomes (5.09–5.56%). Factors in other domains were associated with a slightly decreased population vulnerability, with an exception of the percentage of residents below poverty (1.69–2.05%) for both cardiovascular diseases and mental disorders. We observed the percentage of areas prone to flooding had a greater contribution to the vulnerability for cardiovascular diseases (contribution: 38.45%) and mental disorders (27.43%) than other health outcomes (−3.93–7.64%). 2) Regarding respiratory diseases, although some variables were associated with a decreased vulnerability, we found higher vulnerability to respiratory diseases in communities with higher percentage of green coverage (29.73%) and higher percentage of households living in group quarters

Table 2
Contribution (%) of community factors on the elevated health risk immediately following the storm period.

Factor	Cardiovascular diseases	Respiratory diseases	Injury	Mental disorders	Substance abuse*
Socioeconomic status domain					
Below poverty (%)	1.69	(D)†	4.48	2.05	5.46
Unemployed (%)	−2.71	−4.65	3.98	(D)	5.66
Low Per capita income (USD)	−2.08	−1.70	9.09	−2.60	22.08
No high school diploma (%)	(D)	(D)	6.75	(D)	11.25
Domain total (%)	−3.10	−6.34	24.29	−0.55	44.45
Household composition & disability domain					
Aged ≥65 (%)	(D)	1.18	14.23	(D)	(D)
Aged ≤17 (%)	(D)	−1.83	(D)	(D)	(D)
Disabled (%)	(D)	−2.68	3.06	−3.08	2.72
Single-parent households (%)	−3.16	−3.22	(D)	−2.81	13.41
Domain total (%)	−3.16	−6.55	17.29	−5.88	16.13
Minority status & language domain					
Minority (%)	−5.11	−12.13	(D)	−4.36	5.67
Speak English Less than well (%)	−3.36	−6.67	(D)	−2.21	3.51
Domain total (%)	−8.47	−18.81	0.00	−6.57	9.19
Housing & transportation domain					
Multi-unit structures (%)	12.05	1.93	(D)	11.86	6.20
Mobile home (%)	−2.76	−3.47	−2.47	−7.77	(D)
Crowding (%)	−4.41	−10.37	(D)	−4.74	4.93
No vehicle (%)	5.09	(D)	(D)	5.56	3.52
Group quarters (%)	12.78	8.88	31.39	10.80	6.93
Domain total (%)	22.74	−3.03	28.92	15.71	21.59
Overall (%)	8.01	−34.73	70.51	2.71	91.35
Area prone to flooding (%)	38.45	7.64	(D)	27.43	−3.93
Developed areas (%)	−4.55	−1.75	1.14	−3.78	2.00
Green coverage (%)	(D)	29.73	22.33	−5.74	(D)
Random term	−1.23	0.89	−0.62	−1.56	−1.17

* Substance abuse is an important mental disorder. †(D): A factor was excluded due to its not statistically significant contribution.

(8.88%). 3) We observed that both vulnerability to Sandy-associated injury and substance abuse was higher in communities of higher socioeconomic status. The contribution of socioeconomic factors (particularly the percent of Low Per Capita Income) was 3.98–9.09% for injury, and was 5.46%–22.08% for substance abuse. The minority status and language factors (3.51–5.67%) were significantly associated with higher community vulnerability to substance abuse but not injuries. However, a more important difference between injury and substance abuse was that the percentage of green coverage was a critical predictor for higher vulnerability to injury (22.33%) but was not significant for substance abuse.

Additionally, we found that populations in Sandy-affected areas were more vulnerable to mental disorders, substance abuse, and intestinal infectious diseases within the first year following the Sandy period compared with those living elsewhere. As shown in Table 3, the patterns for the contribution of community factors were similar between different health outcomes. For each health outcome, most factors were associated with an increased community vulnerability, particularly those with a larger contribution, such as percentage of low-income households (contribution: 22.08%) and single-parent households (13.41%) for intestinal infectious diseases and substance abuse, and percentage of population living in multi-unit structures (21.78%) and group quarters (16.32%) for mental disorders.

3.3. Community vulnerability index and validation

The community vulnerability index developed on the contribution-weighted community factors revealed the location of geographical hotspots of high population vulnerability based on the current categorization of the index (Fig. 2). More specifically, Table 4 and Supplemental Table 1 presents the value of *RR* in each cluster, as well as the number and percentage of high vulnerability communities across the study area. Based on our estimates, the percentage of low vulnerability communities was generally lower in clusters with significantly elevated *RR*, whereas the percentage of high vulnerability communities was generally higher in those clusters. For example, elevated *RR* was

Table 3
Contribution (%) of community factors on the elevated health risk in the first year following the storm period.

Factor	Intestinal infectious diseases	Mental disorders	Substance abuse*
Socioeconomic status domain			
Below poverty (%)	5.46	−7.71	5.46
Unemployed (%)	5.66	(D)†	5.66
Low per capita income (USD)	22.08	(D)	22.08
No high school diploma (%)	11.25	(D)	11.25
Domain total (%)	44.45	−7.71	44.45
Household composition & disability domain			
Aged ≥65 (%)	(D)	6.76	(D)
Aged ≤17 (%)	(D)	(D)	(D)
Disabled (%)	2.72	−16.14	2.72
Single-parent households (%)	13.41	(D)	13.41
Domain total (%)	16.13	−9.38	16.13
Minority status & language domain			
Minority (%)	5.67	(D)	5.67
Speak English less than well (%)	3.51	−4.55	3.51
Domain total (%)	9.19	−4.55	9.19
Housing & transportation domain			
Multi-unit structures (%)	6.20	21.78	6.20
Mobile home (%)	(D)	(D)	(D)
Crowding (%)	4.93	(D)	4.93
No vehicle (%)	3.52	9.89	3.52
Group quarters (%)	6.93	16.32	6.93
Domain total (%)	21.59	47.99	21.59
Overall (%)	91.35	26.35	91.35
Area prone to flooding (%)	−3.93	−3.87	−3.93
Developed areas (%)	2.00	(D)	2.00
Green coverage (%)	(D)	(D)	(D)
Random term	−1.17	−3.10	−1.17

* Substance abuse is an important mental disorder. †(D): A factor was excluded due to its not statistically significant contribution.

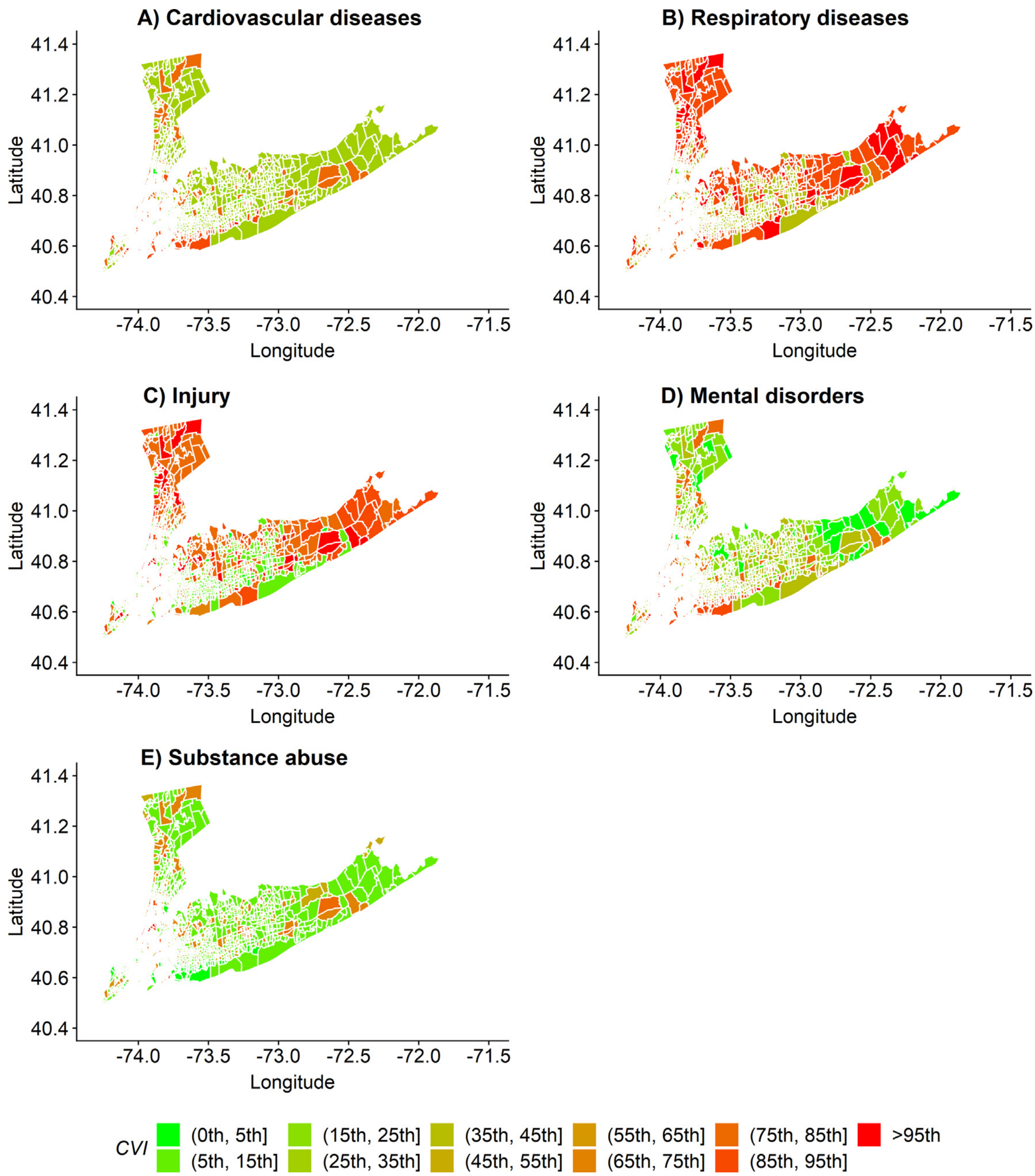

Fig. 2. Community vulnerability index across the study Area: (A) cardiovascular diseases, (B) respiratory diseases, (C) injuries, (D) mental disorders (E) substance abuse. Red colors indicate relatively elevated community vulnerabilities while green colors indicate relatively decreased vulnerabilities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

observed in clusters 6, 10, 12, and 15 for respiratory diseases. The percentage of low vulnerability communities in these four clusters was 0.00% (range: 0.00–5.00%) and was lower than the values for other clusters (9.23%, range: 0.00–54.07%). The percentage of high vulnerability communities was 48.75% (range: 00.00–93.18%) and was higher than values for other clusters (19.11%, range: 00.00–91.07%). Additionally, we found generally higher percentage of high vulnerability communities in geographical clusters 12 and 13 for cardiovascular diseases (40.56%, range: 38.18–42.94%) , cluster 12 for mental disorders (42.65%), cluster 8 for injury (67.57%), and cluster 7 for substance abuse (50.24%), as well as longer-term vulnerabilities to injury and substance abuse (73.68%). Characteristics of clusters were described in Supplemental Tables 2 and 3.

When further evaluating the community vulnerability index with ROC curves, we found the area under curve (AUC) ranged from 0.73 −0.90 for the short-term storm-health associations, and consistently was 0.90 for the association within the first year after the storm period (i.e. selected CVI in Table 5). When we re-estimated the index with all community factors (i.e. regular CVI in Table 5), the improvement in AUC was subtle, as shown in Table 5. For further comparison, we observed AUC for social vulnerability index (SVI) ranged from 0.41 −0.87 for short-term storm-health associations and was 0.57–0.87 for the association within the first year after the storm period.

4. Discussion

4.1. Community vulnerability for different outcomes

In the present study, our major findings revealed that community vulnerability during Superstorm Sandy could be quite different and

Table 4
Summary of short-term associations and the community vulnerability index by cluster.

Cluster	Cardiovascular diseases		Respiratory diseases		Injuries		Mental disorders		Substance abuse	
	RR (95% CI)	HVC* N (%)	RR (95% CI)	HVC N (%)	RR (95% CI)	HVC N (%)	RR (95% CI)	HVC N (%)	RR (95% CI)	HVC N (%)
1	1.02 (0.82, 1.28)	4 (0.91)	1.02 (0.88, 1.18)	0 (0.00)	1.00 (0.87, 1.14)	2 (0.46)	0.96 (0.83, 1.12)	3 (0.68)	0.95 (0.80, 1.13)	66 (15.07)
2	1.18 (0.78, 1.78)	0 (0.00)	1.03 (0.79, 1.36)	0 (0.00)	0.99 (0.82, 1.19)	0 (0.00)	1.04 (0.81, 1.34)	0 (0.00)	0.93 (0.69, 1.26)	6 (2.64)
3	1.04 (0.40, 2.73)	0 (0.00)	1.03 (0.60, 1.76)	16 (66.67)	1.14 (0.83, 1.57)	9 (37.50)	0.75 (0.42, 1.37)	0 (0.00)	0.92 (0.47, 1.82)	2 (8.33)
4	0.79 (0.50, 1.24)	0 (0.00)	0.95 (0.71, 1.27)	0 (0.00)	0.99 (0.83, 1.18)	1 (0.51)	0.96 (0.75, 1.22)	0 (0.00)	1.09 (0.84, 1.42)	54 (27.69)
5	0.97 (0.69, 1.35)	11 (3.62)	1.01 (0.80, 1.28)	21 (6.91)	0.95 (0.81, 1.10)	29 (9.54)	0.98 (0.81, 1.19)	11 (3.62)	1.04 (0.84, 1.29)	11 (3.62)
6	0.97 (0.68, 1.38)	0 (0.00)	1.64 (1.25, 2.16)	0 (0.00)	1.09 (0.94, 1.27)	0 (0.00)	0.95 (0.74, 1.23)	0 (0.00)	0.87 (0.64, 1.17)	0 (0.00)
7	1.22 (0.93, 1.59)	8 (3.83)	1.00 (0.86, 1.15)	8 (3.83)	0.94 (0.81, 1.09)	105 (50.24)	1.15 (0.99, 1.34)	9 (4.31)	1.28 (1.07, 1.52)	154 (73.68)
8	1.62 (0.68, 3.85)	4 (10.81)	0.96 (0.51, 1.79)	24 (64.86)	1.45 (1.05, 1.99)	25 (67.57)	0.98 (0.60, 1.61)	4 (10.81)	0.84 (0.49, 1.46)	13 (35.14)
9	1.27 (0.69, 2.34)	41 (35.65)	1.17 (0.76, 1.79)	36 (31.30)	1.02 (0.82, 1.26)	48 (41.74)	0.89 (0.69, 1.15)	41 (35.65)	0.97 (0.75, 1.24)	2 (1.74)
10	1.22 (0.73, 2.05)	0 (0.00)	1.57 (1.04, 2.38)	82 (93.18)	1.08 (0.89, 1.32)	19 (21.59)	1.07 (0.73, 1.59)	0 (0.00)	1.14 (0.72, 1.79)	0 (0.00)
11	0.89 (0.44, 1.79)	0 (0.00)	1.64 (0.98, 2.74)	51 (91.07)	1.16 (0.93, 1.46)	18 (32.14)	0.94 (0.56, 1.56)	0 (0.00)	0.91 (0.49, 1.70)	0 (0.00)
12	1.48 (1.15, 1.91)	146 (42.94)	1.27 (1.08, 1.49)	56 (16.47)	1.10 (0.98, 1.24)	77 (22.65)	1.20 (1.03, 1.40)	145 (42.65)	0.97 (0.81, 1.15)	30 (8.82)
13	1.90 (1.01, 3.57)	21 (38.18)	0.96 (0.62, 1.49)	28 (50.91)	1.20 (0.92, 1.55)	19 (34.55)	1.34 (0.88, 2.05)	21 (38.18)	1.31 (0.79, 2.17)	8 (14.55)
14	1.03 (0.82, 1.29)	166 (34.51)	1.06 (0.92, 1.22)	15 (3.12)	1.06 (0.94, 1.19)	34 (7.07)	1.00 (0.87, 1.15)	163 (33.89)	0.98 (0.83, 1.15)	85 (17.67)
15	1.19 (0.75, 1.89)	12 (10.34)	1.52 (1.06, 2.16)	94 (81.03)	1.10 (0.92, 1.31)	38 (32.76)	1.33 (0.98, 1.81)	12 (10.34)	0.93 (0.65, 1.35)	0 (0.00)
16	0.75 (0.27, 2.10)	9 (50.00)	1.35 (0.76, 2.42)	9 (50.00)	1.41 (0.90, 2.22)	15 (83.33)	0.79 (0.56, 1.10)	8 (44.44)	0.91 (0.64, 1.29)	11 (61.11)

*HVC, High Vulnerability Communities with CVI above the top 15th percentile.

Table 5
Area under the ROC Curves by Index and Health Outcomes.

	Selected CVI*	Regular CVI	SVI
Cardiovascular diseases	0.78 (0.75, 0.80)	0.78 (0.76, 0.80)	0.51 (0.49, 0.54)
Respiratory diseases	0.73 (0.71, 0.75)	0.73 (0.71, 0.75)	0.41 (0.39, 0.43)
Injury	0.83 (0.75, 0.92)	0.84 (0.76, 0.93)	0.70 (0.62, 0.77)
Mental disorders	0.81 (0.78, 0.83)	0.81 (0.79, 0.83)	0.48 (0.45, 0.51)
Substance abuse	0.90 (0.88, 0.92)	0.90 (0.88, 0.92)	0.87 (0.84, 0.90)
Intestinal infectious diseases (1st year after storm period)	0.90 (0.88, 0.92)	0.90 (0.88, 0.92)	0.87 (0.84, 0.90)
Mental disorders (1st year after storm period)	0.90 (0.88, 0.93)	0.92 (0.90, 0.94)	0.57 (0.53, 0.60)
Substance abuse (1st year after storm period)	0.90 (0.88, 0.92)	0.90 (0.88, 0.92)	0.87 (0.84, 0.90)

* Selected CVI represents CVI based on selected variables; Regular CVI represents CVI based on the full model.

even vary in direction based on health outcomes. More specifically, we found that injury, substance abuse, cardiovascular diseases, and mental disorders increased more in communities of less optimal social environment following the storm period, but respiratory diseases increased more in optimal social environment.

Substance abuse was the most sensitive disease susceptible to many less optimal community indicators after the storm, followed by injury among all the outcomes. Our findings of increased vulnerabilities to substance abuse and injury after Sandy in communities with lower socioeconomic status align with prior findings among residents affected by Hurricane Katrina. Moise and Ruiz (2016) reported significantly higher hospital admission rates for substance abuse disorders after Katrina in communities with higher percentage of residents below poverty than in other communities. Another study in Houston found a disproportional increase in substance use among the economically disadvantaged in contrast to much smaller or no increases in the general populations (Cepeda et al., 2010). A review by Fothergill and Peek 2004 suggested that lower socioeconomic groups were also more likely to suffer from injuries and psychological trauma during natural disasters. According to a report by the Substance Abuse and Mental Health Services Administration (2017), potential reasons for higher rates of substance use and injury among residents of lower socioeconomic status, included perceiving more risk and feeling more concern regarding disasters, performing jobs that elevated exposure risk, living in more fragile housing, less likely to take preparedness measures, lower access to resources, and decrease likelihood of responding to warnings and evacuation (Fothergill and Peek, 2004; Hallegatte et al., 2016; Lowe et al., 2014).

Different from traditional assumptions that high vulnerability to health problems always occurred in communities of poor social environment, we found that respiratory diseases increased more in communities of optimal social environment. Likewise, nearly all or most social factors consistently indicated a higher vulnerability to respiratory diseases in communities with better social environment. Logan and Xu

(2015) suggested that wealthier communities were more likely to reside near rivers or lakes, which was usually perceived as an amenity. However, catastrophic storms may bring both chemical and biological pollutants into the water (The Associated Press, 2018). Higher exposure to contaminated aerosols was a plausible interpretation for higher vulnerability to adverse respiratory outcomes (Carwile et al., 2014; European Lung Foundation, 2011; Rose, 1992; Wesselink et al., 2018). Another possible reason was that wealthier individuals who adapted to a generally physical static and high electrical dependence residential environment tended to be more susceptible to sudden environmental changes, such as extended power outages due to storms. These individuals often include residents who are dependent on electricity to manage diseases, such as asthma and COPD (Lin et al., 2011).

4.2. Comparison of different community domains and factors

We found that socioeconomic status, housing and transportation factors may have the largest contributions on the vulnerability to multiple health outcomes among all four domains of factors. In contrast to equal-contribution assumption of previous studies, our finding emphasized the importance of considering the contribution variation across domains (Barry et al., 2011b; Nayak et al., 2018). Additionally, contributions of these domains were generally higher for certain outcomes, suggesting that these domains may have good capability of identifying high vulnerability to certain outcomes, and distinguishing these outcomes from others. For example, the socioeconomic status domain had large contributions on the vulnerability to injury and substance abuse but small contributions to other outcomes. This suggests that the socioeconomic status factors were sensitive indicators for vulnerability to injury and substance abuse. Similarly, we observed that factors among the minority and language domain, and the housing and transportation domain were sensitive indicators for respiratory diseases. Conversely, our results suggested that the household composition and disability domain was less important, compared with other domains.

In terms of vulnerability factors within the domain, we found that low per capita income, percentage of population without a high school diploma, living in multi-unit structures and group quarters, the percentage of areas prone to flooding, and the percentage of green coverage are dominant predictors for community vulnerability to multiple health outcomes. For instance, we found that communities with higher percentage of low education, low income, unemployment, and below poverty are more vulnerable to the adverse effects of Superstorm Sandy on multiple outcomes including substance abuse and injuries. These findings were consistent with prior research among residents affected by other catastrophic storms (Cepeda et al., 2010; Moise and Ruiz, 2016; Zoraster, 2010). The higher vulnerability in poor neighborhoods could be explained by lack of access to adequate medical care, decreased likelihood of receiving adequate information on disaster preparedness and management, and encountering financial difficulty for housing repairs (Substance Abuse and Mental Health Services Administration, 2017).

The present study showed that communities with higher percentages of residents in multi-unit structures (e.g. densely-populated high-rise apartments) or group quarters (e.g. nursing facilities) were more vulnerable to cardiovascular diseases, injuries, mental disorders, and substance abuse. A plausible interpretation is that many residents in these places, such as the long-term nursing facilities had chronic cardiovascular diseases or mental disorders which were more likely to exacerbate during extreme events (Dosa et al., 2010). Another reason was that most residents in nursing facilities had significant functional limitations and special needs, which limited their ability to respond appropriately during emergencies, as suggested by Barry et al. (2011a). Crowding within these places usually exacerbate these limitations (Gutmann, 2006).

Additionally, our estimates suggested that communities with higher percentage of area prone to flooding were more vulnerable to cardiovascular and mental disorders whereas those with higher percentage of green coverage tended to be more vulnerable to injury and respiratory diseases. The association between flooding hazards and the elevated vulnerability to cardiovascular and mental disorders was previously reported by Harris et al., (2018); Nagayoshi et al., (2015); Nakamura et al., (2012); Stanke et al., (2012). There are also evidence supporting the biological pathway between green coverage and vulnerability to injury and respiratory diseases. Higher percentage of green coverage implies a higher percentage of area prone to tree damage which can pose a critical health risk on residents during a storm. For instance, damage and cleanup related to tree fallings is one of the most common causes of injuries and deaths (Goldman et al., 2014; Issa et al., 2018; Marshall et al., 2018). Meanwhile, tree contact is among the top causes of power outage which was suggested to be associated with significant increases in the risk of respiratory disease exacerbations, for example, as a result of interruptions in electricity-dependent oxygen supply and medication nebulizers (Lin et al., 2011). Therefore, pre-event evacuation and reducing outdoor activities during storms may be important for residents in those areas, particularly for those with functional limitations or in need of electricity-dependent life-support.

Our estimates show that not all traditionally perceived risk factors at the individual level significantly affected disease vulnerability at the population level. For example, the percentage of people ≥ 65 years of age or those < 17 years did not significantly alter the community vulnerability to most health outcomes following the storm period. We were also surprised to find that communities with higher percentage of people who spoke English less than well and being of minority population even had lower risks for multiple diseases. The mechanism remains unclear, however, limited access to medical resources due to language and cultural barriers is among the most plausible interpretations (de Moissac and Bowen, 2017; Fofana, 2017; Saha et al., 2007). As a result, outcomes for these groups are not likely to be fully reflected in the data. Alternatively, some non-English language-speaking communities may be relatively closely knit, with high social capital and cultures emphasizing mutual assistance (Aldrich, 2012; Bach, 2015). These findings highlighted the importance of considering the direction of vulnerability factors rather than simply assuming certain factors were risk or protective.

4.3. Community vulnerabilities to short-term and longer-term effects

We found that community vulnerability to the effects of storm on health could vary by health outcomes. More specifically, we observed that community factors significantly affect residents' vulnerabilities to multiple short-term health outcomes after the storm period, including cardiovascular and respiratory diseases, injury, mental health, and substance abuse. However, we only found longer-term vulnerabilities to mental disorders, substance abuse and intestinal infectious diseases.

Our findings on the short-term vulnerabilities align with previous research which suggested that the impact of catastrophic storms on physical wellness, such as injury, respiratory health, and cardiovascular health generally occurs shortly after the storm made landfall (Lempert and Kopp, 2013; Swerdel et al., 2014). Currently, there remains no evidence that physical issues could last long after the removal or significant decrease in environmental exposures. Our estimates suggested no significant short-term community vulnerabilities to intestinal infectious diseases, which also was consistent with previous findings. Bloom et al. (2016) and CDC's report (CDC, 1986) suggested potential reasons included increased vigilance and public health measures, as well as limited and mostly short-term population displacement which may have mitigated the risk of intestinal infectious diseases.

Our findings on longer-term vulnerabilities to intestinal infectious diseases and mental disorder were well expected. These longer-term vulnerabilities were more likely due to the subsequent changes following the event such as decreased water sanitation, property damage, and other related factors. For example, storms were reported to significantly reduce water sanitation and bring high density of evacuees crowding into shelters, which was considered to be associated with increased risk of intestinal infectious diseases in longer-term recoveries (The Associated Press, 2018). Mental disorders such as depression, anxiety and substance use disorders usually last much longer than other health concerns, particularly among those who suffered from severe property damage or the loss of loved ones during catastrophic storms (LaJoie et al., 2010; Rhodes et al., 2010). Additionally, the positive associations between top contributors and longer-term vulnerability to intestinal infectious diseases and mental disorders suggest that communities of lower socioeconomic status may be more vulnerable to these outcomes for longer periods after the storm.

4.4. Geographic difference of community vulnerability

We found substantial geographical variations in the community vulnerability index for multiple health outcomes. Specifically, our results suggest a higher vulnerability to cardiovascular diseases and mental disorders in clusters 12 and 13; respiratory diseases in clusters 6, 10, 12, and 15; injury in cluster 8, and substance abuse, and longer-term vulnerabilities in cluster 7. These spatial variations were consistent with our findings on the contribution of major community factors. For example, cluster 7 was identified with the largest number of elevated vulnerabilities including a short-term vulnerabilities and two longer-term vulnerabilities. Our estimates on the weighting of community factors suggested that these vulnerabilities were potentially related to low socioeconomic conditions. Meanwhile, the description of community characteristics at cluster level showed the per capita income for the cluster 7 was the lowest among all clusters while other indicators, such as unemployment rate and limited education rate in cluster 7 were much higher than other clusters, representing a relatively lower socioeconomic status for cluster 7.

4.5. Community vulnerability index development and implication

Compared with existing population vulnerability indices (Barry et al., 2011a; Nayak et al., 2018), our new community vulnerability index was developed for specific health outcomes and specific exposures. Both the weight and its direction for each community factor was included in index development.

We found that the new community vulnerability index tended to be more robust and had better predictive performance and greater reliability for complicated factor-vulnerability associations relative to existing indices. ROC curves for the new index showed an AUC significantly greater than 0.70 for all outcomes. Although there is no gold standard to define a good predictive performance, generally an index with AUC greater than 0.70 was deemed an appropriate index for health studies, as reported in our previous studies (Jin et al., 2017; Yao et al., 2018, 2017). In contrast, existing indices, represented by the SVI, may only be valid when all community factors were associated with higher population vulnerability, such as for the vulnerability to longer-term risk of intestinal infectious diseases and both short-term and longer-term risk of substance use disorders. However, the SVI may not truly capture the population vulnerability in all other situations. For instance, the weights of most community factors were below zero for the vulnerability to respiratory diseases. In this situation, the AUC for CVI was 0.73 (95% CI 0.71, 0.75), whereas that for SVI was 0.41 (95% CI 0.39, 0.43) which was significantly smaller than 0.5 and suggested that SVI tended to misidentify low vulnerability communities as high vulnerability ones, and vice versa. Similarly, the SVI for mental disorders (0.48, 95%CI 0.45, 0.51) covered 0.5, which suggested that SVI may identify mental-disorder vulnerable communities at random.

The weights and index obtained in this study not only can be used in the same area for future pre-storm preparations, but also provide insight into population vulnerability to multiple catastrophic storm-related disease groupings in other areas. Our study area is diverse in social environment covering a large heterogeneous racial, ethnic, and socioeconomic population. Our study outcomes are among the most current pressing public health issues. Our procedures overcome three major limitations from the existing methodologies of population vulnerability assessment. Therefore, the community vulnerability index could be a great representative of indexes developed for diverse environmental context.

4.6. Strengths and uncertainties

Our study has several strengths including a large sample size and to the best of our knowledge the first study evaluating community vulnerability to catastrophic storms by comparing multiple health outcomes using innovative methods. Specifically, we used distributed lag nonlinear models in the initial step to catch not only the immediate health impact of catastrophic storms at landfall but also the cumulative impact over days following the storm, which minimized the possibility of underestimation. We used boosted regression tree models, an improved big data analysis technique for the assessment of contributions of community factors. This method was based on a flexible binary-split algorithm that can generate robust estimates in the presence of outliers, missing values, or collinearity issues that arise from the community survey data.

Although our study provides new insights, several methodology uncertainties should be acknowledged. First, we evaluated the storm-health associations on the spatial cluster level, rather than county or census tract levels which are potentially more appealing to policy makers. However, census tract level analysis was limited by the daily sample size while county level analysis may increase ecologic fallacies without considering the intracounty variation in population vulnerability. Second, assigning the same health risk-elevated and unelevated status for a cluster to all census tracts (e.g. communities) within that cluster likely resulted in exposure misclassification. To minimize this potential bias, we (1) classified similar census tracts into the same cluster through clustering analysis on major community factors based on the assumption that communities with similar characteristics also have similar vulnerability (Barry et al., 2011a; Emrich, 2015; Guillard-Gonçalves et al., 2015); and (2) stratified the clustering analysis by percentage of areas prone to flooding, an important predictor for the impact of storms to further improve the homogeneity of each cluster. Third, including numerous variables in a single model may increase the possibility of collinearity issues and uncertainty of effect estimate. We addressed this issue through (1) checking the correlation between each pair of variables to exclude those highly correlated to other multiple factors; and (2) using a novel machine-learning technique to exclude factors with smaller contribution than the random term, and assigning smaller weights to less important factors to further compress the impact of them in developing the final index. This study was conducted at a high resolution-census tract level where high-resolution storm intensity data (e.g. high speed winds, flood peak) were not available. However, we controlled multiple variables related to the storm intensity in the overall association assessment, including wind speed, rainfall, temperature, air pollutions, and other related variables, which to some extent could reduce the impact of the absence of high-resolution storm intensity data. Lastly, results should be interpreted cautiously for studies focusing on the long-term health effect of an event which may be confounded by changes in community characteristics. Our study is not an exception. However, the current study only investigated the health impact of Sandy over one year. Community characteristics such as socioeconomic status, demography and landscape were not likely to change substantially within a single year.

5. Conclusion

This study suggests that substance abuse was the most sensitive disease susceptible to many less optimal community indicators after the storm, followed by injury, cardiovascular diseases, and mental disorders, whereas respiratory diseases were higher in communities with better social environment. Low per capita income, the percentage of low-educated population or those living in multi-unit structures or group quarters, the percentage of areas prone to flooding and the green coverage are dominant predictors for community vulnerability to these health outcomes. Among all outcomes, we found both short-term and long-term increased vulnerabilities for mental disorders including substance abuse, and found only long-term vulnerabilities for intestinal infectious diseases and only short-term vulnerabilities for all others. The community vulnerability index based on this information has an appropriate predictive performance.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2019.105285.

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