The Geography of Mental Health and General Wellness in Galveston Bay After Hurricane Ike: A Spatial Epidemiologic Study With Longitudinal Data

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ORIGINAL RESEARCH

The Geography of Mental Health and General Wellness in Galveston Bay After Hurricane Ike: A Spatial Epidemiologic Study With Longitudinal Data

Oliver Gruebner, Dr rer nat; Sarah R. Lowe, PhD; Melissa Tracy, PhD; Magdalena Cerdá, DrPH; Spruha Joshi, MPH; Fran H. Norris, PhD; and Sandro Galea, DrPH

ABSTRACT

Objectives: To demonstrate a spatial epidemiologic approach that could be used in the aftermath of disasters to (1) detect spatial clusters and (2) explore geographic heterogeneity in predictors for mental health and general wellness.

Methods: We used a cohort study of Hurricane Ike survivors (n = 508) to assess the spatial distribution of postdisaster mental health wellness (most likely resilience trajectory for posttraumatic stress symptoms [PTSS] and depression) and general wellness (most likely resilience trajectory for PTSS, depression, functional impairment, and days of poor health) in Galveston, Texas. We applied the spatial scan statistic (SaTScan) and geographically weighted regression.

Results: We found spatial clusters of high likelihood wellness in areas north of Texas City and spatial concentrations of low likelihood wellness in Galveston Island. Geographic variation was found in predictors of wellness, showing increasing associations with both forms of wellness the closer respondents were located to Galveston City in Galveston Island.

Conclusions: Predictors for postdisaster wellness may manifest differently across geographic space with concentrations of lower likelihood wellness and increased associations with predictors in areas of higher exposure. Our approach could be used to inform geographically targeted interventions to promote mental health and general wellness in disaster-affected communities. (*Disaster Med Public Health Preparedness*. 2016;page 1 of 13)

Key Words: natural disasters, geographic mapping, mental disorders, psychological resilience, post-traumatic stress disorders

The mental health consequences of disasters include psychological symptoms such as post-traumatic stress symptoms (PTSS) and depression.[1-4] Recent literature in the context of disasters has explored psychological *resilience*, defined as low levels of a given symptom or problem over time, with only minimal elevations in symptoms limited to the time period during the disaster and its immediate aftermath.[5-7] However, evidence suggests that a substantial proportion of disaster survivors exhibit *mental health wellness*, that is, resilience across multiple mental health conditions, and *general wellness*, that is, resilience across mental health and other domains, such as physical health and role functioning. By focusing on wellness, versus trajectories of a single disorder, we can more accurately evaluate the extent to which a community has recovered after a disaster and identify targets for public health interventions.[8]

Despite the potential implications of investigating postdisaster wellness, to our knowledge, only one published study—an analysis of a population-based sample of Hurricane Ike survivors—has done so empirically.[9] In this study, nearly 75% of participants had membership in the resilience trajectory for PTSS, around 58% for depression, around 53% for days of poor health, and about 45% for functional impairment. This resulted in the classification of over 51% of the participants exhibiting mental health wellness and of about 26% exhibiting general wellness. Predictors of wellness included age, predisaster mental health, and disaster experiences, with variation in the strength of associations between predictors and mental health versus general wellness.[9]

In the current study, we expand upon this previous analysis by taking a spatial epidemiologic perspective on wellness. Through spatial analysis, researchers can provide insight into the patterning and predictors of wellness across geographic space. To our knowledge, no studies to date have applied a spatial epidemiologic perspective to the concept of postdisaster wellness, and only 3 have investigated spatial variation in post-disaster mental health. Curtis et al[10] mapped potential vulnerability factors in the aftermath of Hurricane Katrina to indicate which neighborhoods in New Orleans might have had the most severe postdisaster stress-related health outcomes. Two other studies applied a spatial approach and showed that greater proximity to the disaster site was associated with increased postdisaster psychopathology.[11,12] These studies included only cross-sectional data, preventing the investigation of geographic variation in trajectories of mental health. Furthermore, none of these studies included other indicators of wellness, such as physical health and role functioning, nor did they explore geographic variation in associations between predictors and mental health outcomes.

Therefore, there remains much we do not know about the spatial patterning of postdisaster mental health and general wellness. A spatial epidemiologic approach to understanding wellness could be applied in the aftermath of disasters in at least 2 ways. First, this approach could help to identify and target communities at risk for poor wellness. For example, it is possible that residents of geographic areas that were more severely damaged by the disaster might be less likely to exhibit wellness than residents of other areas. Such spatial clusters indicate the magnitude, geographic space (spatial extent), and the geographic location of risk for communities and could help to determine which communities are at increased risk of postdisaster adversity.

Second, a spatial epidemiologic approach could provide important insights into which individuals *within* different geographic areas are at increased risk. For example, the association between individual and socio-ecological factors and postdisaster wellness might vary across communities and geographic areas, such that some factors might be more strongly associated with wellness in one neighborhood than in another. Knowledge of spatial heterogeneity in predictors could help to target subgroups within a particular geographic area at risk for poor mental health and general wellness.

The overall aim of this study was to demonstrate how spatial analysis could be used to identify patterns of mental health and general wellness, and predictors of wellness, across geographic space in the aftermath of disasters. We used data from survivors of Hurricane Ike, a strong category 2 storm with sustained winds of 110 miles per hour that hit Galveston and Chambers counties in Texas in 2008 with a category 5 equivalent storm surge. The large wind field of over 120 miles away from the center pushed water toward the coastline well before Hurricane Ike made landfall. Figure 1 shows the probabilities for storm surge in the Galveston region at 12-hour intervals between September 10 and 13, 2008. Hurricane Ike made landfall at 2:10 AM on September 13, crossing the Bolivar Peninsular with a high storm surge of 15 feet. Figure 2A shows the storm track and the wind radii away from this track. The hurricane then travelled north to Galveston Bay and passed the east side of Houston. The hurricane and its aftermath led to the displacement of 16,000 families and nearly 200 deaths.[15] Over $29.6 billion was lost in personal and infrastructure damage.[15-17]

To investigate the geographic variability of wellness in this region, the goals of this study were (1) to identify spatial clusters of mental health and general wellness after Hurricane Ike based on longitudinal data, (2) to test associations between predictors and mental health and general wellness, and (3) to explore the geographic heterogeneity in the strength of associations between predictors and outcomes.

METHODS

Study Design, Sample, and Data Collection

We conducted a longitudinal study in the 2 Texas counties, Galveston and Chambers, where Hurricane Ike hit the hardest. The counties were divided into 5 strata that included 80 area segments. Within these segments, 2263 households were contacted as detailed elsewhere.[18] Oversampling was performed in areas closer to the shoreline and therefore sampling was not proportional to population size. No significant differences were detected between the study sample and the 2000 US Census population in the sampling frame of Galveston and Chambers counties.[18] Participants needed to be 18 years of age or older and had to be living in Galveston County or Chambers County for at least 1 month before the hurricane to be eligible for this study. Interviews were conducted by use of a computer-assisted interview system. After the study was described to the participants at each wave, verbal informed consent was obtained. For wave 1 (W1), 658 participants completed interviews that were conducted approximately 2 to 5 months after Hurricane Ike, resulting in a response rate of 43%.[19] Stratum one thereby had a response rate of 47%, stratum two 40%, stratum three 46%, stratum four 49%, and stratum five 38%. For wave 2 (W2), follow-up interviews were conducted at 5 to 9 months (n = 529), and for wave 3 (W3), 14 to 19 months (n = 487) after the disaster.

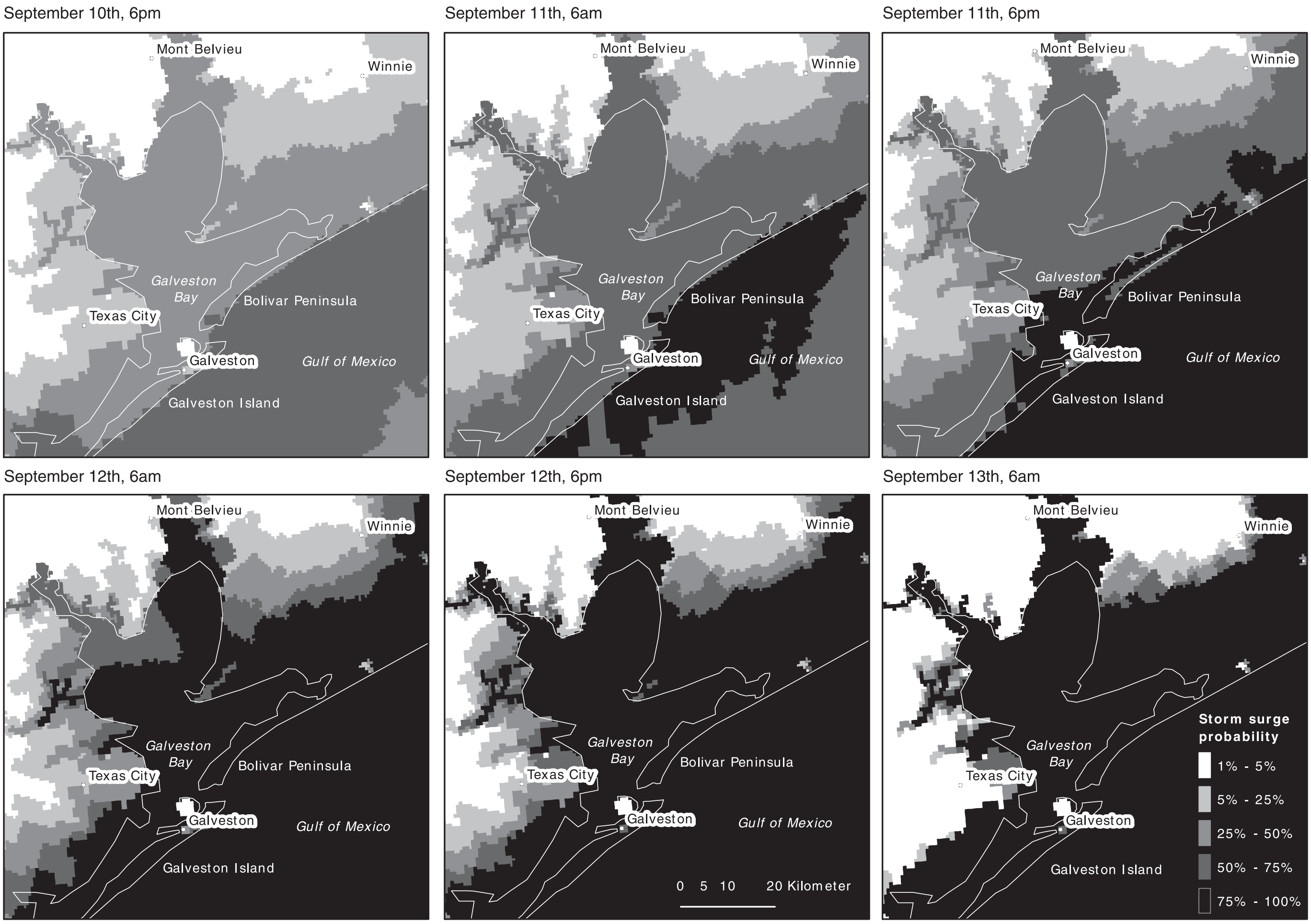
Geographically, the sampling strategy sometimes included multiple respondents from the same apartment building, but never more than one respondent from the same household. For this study, we restricted the analysis to participants with nonmissing data on all explanatory variables from W1 (n = 561). We geocoded the participants' addresses, and if more than one participant lived at the same location (eg, in the same apartment building), we randomly selected one participant to be included in the analysis. This led to a final sample of 508 respondents. Figure 2B depicts the geographic locations of participants at the time of the hurricane. All study procedures were approved by the institutional review boards of the University of Michigan, Dartmouth College, and Yale University.

Mental Health and General Wellness

Mental health and general wellness were used as outcome variables in this study and were previously found by a

FIGURE 1

Storm Surge Probabilities for the Galveston Area in 12-h Intervals Between September 10 and 13.



Source: National Hurricane Center[13]

group-based modeling approach detailed elsewhere.[9] In brief, 4 outcomes were assessed at W1, W2, and W3. PTSS related to Hurricane Ike was assessed with the Post-Traumatic Stress Disorder (PTSD) Checklist-Specific version (PCL-S).[20] Although this checklist is typically assessed in reference to the prior month, we modified this for the current study so that W1 questions were asked in reference to the period since the hurricane, and at W2 and W3, the period since the previous interview.

Depressive symptoms in the past month were assessed with the Patient Health Questionnaire (PHQ-9).[21] Functional impairment in the past month was assessed with 6 items from the Short Post-Traumatic Stress Disorder Rating Interview-Expanded version (SPRINT-E).[22] Finally, days of poor health in the past month before the interview were assessed with 1 of the 4 items that make up the Centers for Disease Control and Prevention's Health-Related Quality of Life-4 (CDC HRQOL-4).[23]

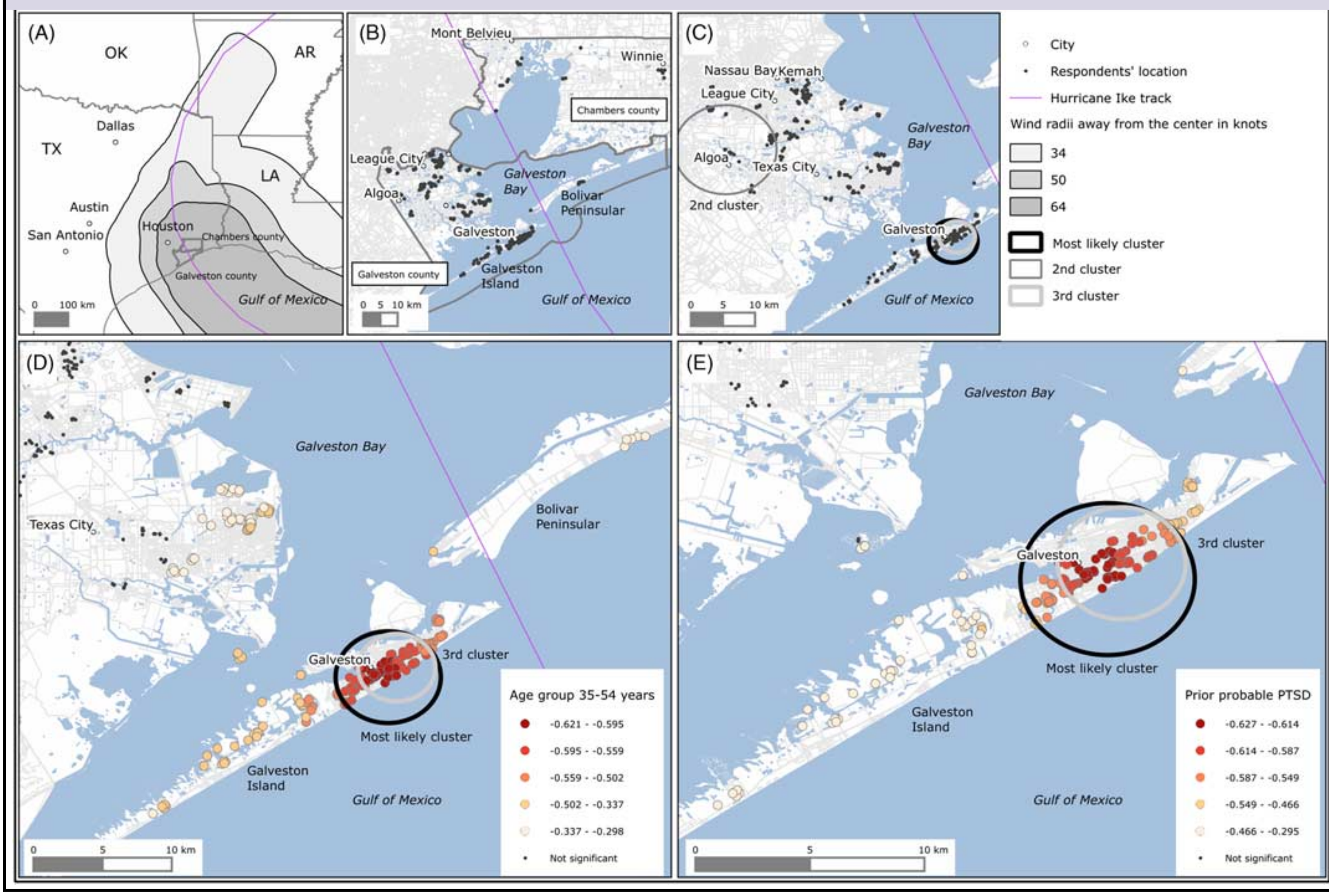
Latent class growth analysis was used to identify latent trajectories in each of the 4 outcomes over the 3 waves of the study. A resilience trajectory of consistently low symptoms or problems over the 3 waves was evident for each outcome, and participants were categorized into those whose most likely trajectory was resilience, versus another trajectory, for each outcome. Dichotomous variables for mental health wellness (most likely membership in the resilience trajectory for both PTSS and depression) and general wellness (most likely membership in the resilience trajectory for all 4 outcomes) were then created[9] and were added to the complete and geographically unique dataset from W1 ($n = 508$).

Explanatory Variables

We included the same set of explanatory variables as in the prior study,[9] which contains additional information about the reliability and validity of measures. Explanatory variables were assessed at W1 and included participants' demographic

FIGURE 2

Hurricane Track, Study Area, Mental Health Wellness Clusters, and Predictors. Abbreviation: PTSD, post-traumatic stress disorder. (A) Hurricane Ike track, wind swath, and wind radii over the study area. (B) Study area and respondents' locations. (C) Spatial clusters of mental health wellness. (D) Spatial heterogeneity of the geographically varying predictor age group of 35 to 54 years and spatial clusters of low likelihood mental wellness. (E) Spatial heterogeneity of the geographically varying predictor predisaster probable PTSD and spatial clusters of low likelihood mental wellness. Note: *N* = 152, ie, 30% of the total sample population was used as the spatial neighborhood definition. Shaded points in (D) and (E) represent the strength of significant regression coefficients associated with mental health wellness at each respondent's location. Source: National Hurricane Center[14] and authors' own survey. Note that respondents' locations have been altered to preserve confidentiality.



characteristics, predisaster trauma exposure, predisaster mental health (PTSD and major depression), hurricane-related exposures, and social assets in the community (Table 1). Demographic variables included age, sex, race/ethnicity, and education.

Predisaster trauma exposure was assessed by using a traumatic events inventory[24] in which participants indicated (yes/no) whether they had experienced 10 events (eg, sudden bereavement of family or friends, serious accident) in their lifetime before Hurricane Ike. The total number of predisaster trauma events was then divided into 3 categories for this analysis: 0 to 1 traumas, 2 to 3 traumas, and 4 or more traumas. PTSS was assessed with a modified version of the PCL-S[25] in reference to the predisaster traumatic event that participants designated as the "worst." *Diagnostic and Statistical Manual of Mental Disorders*, 4th edition, text revision (DSM-IV-TR) criteria were applied to determine whether participants had probable predisaster PTSD. The PHQ-9 was used to assess participants' predisaster major depression in reference to any 2-week period in their lifetime. Participants were classified as having predisaster probable major depression when they scored 10 or higher and indicated that symptoms occurred together with onset prior to Hurricane Ike.[26]

For hurricane-related trauma, participants indicated (yes/no) whether they had faced any of the following: physical injury, death of a family member or a close friend, seeing dead bodies, or a family member or close friend injured as a result of Hurricane Ike.

TABLE 1

Descriptive Statistics for All Variables Included in the Study[a]

Variable	No. (%) or Mean ± SD
Age	
18–34 years	124 (24.4%)
35–54 years	185 (36.4%)
55 years or older	199 (39.2%)
Sex	
Women	290 (57.1%)
Men	218 (42.9%)
Race/ethnicity	
White non-Hispanic	327 (64.4%)
Black non-Hispanic	69 (13.6%)
Hispanic	88 (17.3%)
Other non-Hispanic	24 (4.7%)
Highest level of education completed	
Less than high school	56 (11%)
High school degree or equivalent	110 (21.7%)
More than high school degree	342 (67.3%)
Number of traumatic events before Hurricane Ike	
0–1	144 (28.3%)
2–3	202 (39.8%)
4 or more	162 (31.9%)
Predisaster probable PTSD	
No	446 (87.8%)
Yes	62 (12.2%)
Predisaster probable major depression	
No	394 (77.7%)
Yes	114 (22.4%)
One or more hurricane-related trauma	
No	451 (88.8%)
Yes	57 (11.2%)
Without any resource for more than 1 week	
No	229 (45.1%)
Yes	279 (54.9%)
Any personal property loss	
No	69 (13.6%)
Yes	439 (86.4%)
Any loss of sentimental possessions or pets	
No	355 (69.9%)
Yes	153 (30.1%)
Financial loss as a result of Ike	
No	344 (67.7%)
Yes	164 (32.3%)
Increased demands or relationship problems	
No	338 (66.5%)
Yes	170 (33.5%)
Displaced from home as a result from Ike	
No	87 (17.1%)
Yes	421 (82.9%)
Peri-event emotional reactions	
Low	306 (60.2%)
Medium	107 (21.1%)
High	95 (18.7%)
Social support	2.5 ± 0.03
Collective efficacy	3.9 ± 0.04
Mental health wellness	
Poor	226 (44.5%)
Good	282 (55.5%)
General wellness	
Poor	356 (70.1%)
Good	152 (29.9%)

[a]Abbreviation: PTSD, post-traumatic stress disorder. n = 508.

For hurricane-related stressors, participants indicated (yes/no) whether due to the hurricane they (1) were without any resource (food, water, shelter, electricity) for more than 1 week, (2) had any personal property loss, (3) had any loss of sentimental possessions or pets, (4) had financial loss, (5) had increased demands or relationship problems, or (6) were displaced from home. Each stressor was included as a separate predictor in our study.

To assess peri-event emotional reactions, we applied the 4-item STRS (shortness of breath, tremulousness, racing heart, and sweating) checklist.[27] Participants were asked to recall how they felt at the time of the hurricane and in the following few hours in the aftermath, with a focus on shortness of breath; trembling, shaking, or buckling knees; heart pounding or racing; and sweaty palms or other sweating. This measure was categorized into tertiles with high, medium, and low levels of peri-event emotional reactions.

Community-level social assets included social support and collective efficacy. Social support was assessed by using the Inventory of Postdisaster Social Support, which included 11 items, such as (1) "How often did family members or friends express interest and concern in your well-being?" or (2) "…offer or provide you with a place to stay?"[28,29] Possible responses ranged from never (1) to many times (4), resulting in a mean score ranging from 1 to 4. For measuring collective efficacy, we applied a 10-item scale with items assessing social cohesion and trust (eg, "this is a close knit or unified neighborhood," rated from 1 = strongly disagree to 5 = strongly agree) and informal social control (eg, "If a group of neighborhood children was skipping school and hanging out on a street corner, how likely is it that your neighbors would do something about it?" rated from 1 = very unlikely to 5 = very likely).[30-32] Mean values of the 10 items were calculated, ranging from 1 to 5. Because social support and collective efficacy are conceptualized as functioning at the community level rather than the individual level,[8,22] aggregate means at the census block level for each measure were included in the analysis.

Analytical Methods

In this study, we replicated the nonspatial analysis of Lowe et al[9] with a spatial analysis by using an unweighted sample owing to methodological restrictions and to the analysis being conducted at the person level. We first explored spatial clusters of mental health and general wellness as defined in the previous analysis.[9] Spatial approaches require a definition of the spatial neighborhood, that is, a specification of sample points considered to be neighbors based on adjacency or based on spatial weights that place more weight on locations that are closer in space to a particular respondent's location than to those that are more distant in space.[33,34] To identify spatial clusters of mental health and general wellness, we applied the spatial scan statistic (SaTScan)[35,36] and defined the spatial neighborhood of a particular location through a circular spatial scanning window based on adjacency to other respondents' locations. For each location, the radius of the window varied continuously in size from zero to a maximum window size, thereby being flexible both in location and size.[36] Within the maximum spatial scanning window, we utilized a set of different maximum reported cluster sizes (neighborhood definitions), because model outcomes are sensitive to the neighborhood used.[34,37] The set of maximum reported cluster sizes included 51, 102, 152, and 203 observations, that is 10%, 20%, 30%, and 40% of the total population ($n = 508$) in the entire area, respectively. To adjust for the multiple testing of these different neighborhood definitions, we kept the maximum spatial scanning window size at all times at 40% of the total population evaluated. We used a purely spatial approach scanning for clusters with higher or lower likelihood of wellness by using the Bernoulli model. The most significant cluster, for example, was thereby assessed with a likelihood ratio test based on means of a Monte Carlo approach with 9999 permutations.[36]

We then applied a 3-step analysis to explore spatial heterogeneity in predictors of mental health and general wellness. Specifically, we considered the explanatory variables from the final models in Lowe et al[9] for the spatial analysis of both outcomes (mental health and general wellness). First, we fit nonspatial multivariable logistic regression models including all explanatory variables as predictors and mental health and general wellness as dependent variables. Second, we applied a forward/backward model selection approach to identify the best model for each outcome based on lowest AIC values. Multivariable logistic regression analyses were done with the package MASS[38] in the statistical programming language and environment R.[39] Finally, we applied logistic geographically weighted regression (GWR) with standardized predictors for the best models found above. In contrast to nonspatial logistic regression models, where coefficients are estimated for the entire study area (globally fixed), in GWR, regression coefficients are estimated at each respondent's location (locally varying), allowing for the exploration of predictors' geographic heterogeneity across the study area.[40]

In GWR we defined the spatial neighborhood through a spatial weights matrix that was calculated at each respondent's location by using a kernel function that places more weight on locations that are closer in space to that respondent's location than to those that are more distant in space.[41] We utilized an adaptive kernel function that in this context adapted for varying distances between the locations with a bandwidth parameter that determined the maximum spatial range of the kernel (comparable to the maximum spatial scanning window as it was used in SaTScan). Again, we used a set of several single bandwidths in various analyses applying the k-nearest neighbors of a respondent's location with either 102, 152, or 203 observations, that is, 20%, 30%, or 40% of the population, respectively. We considered 10% of the population with 51 nearest neighbors insufficient for local regression estimation in GWR owing to the rather limited number of degrees of freedom in the model and hence omitted these for the GWR analysis. We applied a local-to-global variable selection procedure for both outcomes that conducts a series of model comparison tests between the originally fitted model and a model in which a geographically varying variable has been changed to a fixed variable with all other variables remaining unchanged.[42] Model performance was thereby evaluated based on lowest AIC values at each step. The variable selection from the geographically varying predictors to the geographically fixed ones was repeated until there was no candidate of such a predictor being changed or no improvement gained.[43] GWR analysis was applied with GWR4 software.[44]

RESULTS

Spatial Clusters of Mental Health and General Wellness

We identified significant spatial clusters for both mental health wellness (membership in the resilient trajectory for both PTSS and depression) and general wellness (membership in the resilient trajectory for all 4 outcomes). Spatial patterns were consistent across the different neighborhood definitions used and varied only systematically in size depending on the maximum reported cluster size (Table 2). Therefore, we report the results solely from 30% of the population ($n = 152$), owing to better comparability with the other findings on spatial heterogeneity of wellness predictors as detailed below.

We found 2 clusters of low likelihood mental health wellness (first and third clusters in terms of significance) and one cluster of low likelihood general wellness (first cluster). Furthermore, we found one cluster each of high likelihood mental health and general wellness (both second clusters in terms of significance). We noted that the clusters of high likelihood mental health and general wellness tended to be of a larger geographic size than the clusters of low likelihood wellness (Table 2). Whereas spatial clusters of low likelihood mental health and general wellness were found exclusively on Galveston Island (Figures 1C-E and 2A-D), the relatively larger clusters of high likelihood wellness were found in the hinterland north of Texas City: a mental health wellness cluster was found around the city of Algoa (Figure 2C) and a general wellness cluster was found in the triangle between League City, Nassau Bay, and Kemah (Figure 2B).

Geographic Variability of Associations Between Explanatory Variables and Wellness

Associations Between Explanatory Variables and Mental Health and General Wellness

Predictors of mental health and general wellness from multivariable logistic regression models are presented in Table 3. Respondents were significantly less likely to exhibit mental health wellness when they were 55 years or older (compared to 18–34-year-olds), had a high school degree or equivalent (compared to less than a high school degree), had predisaster probable psychopathology (predisaster probable

TABLE 2

Spatial Scan Statistics Results for Different Maximum Spatial Scanning Window Sizes[a]

	Mental Health Wellness[b]				General Wellness[b]			
	10%	20%	30%	40%	10%	20%	30%	40%
Most likely cluster								
Radius, km	1.27	7.93	3.79	3.79	1.63	1.64	1.64	15.37
Population	44	89	128	128	56	59	59	219
Wellness cases	11	67	46	46	3	3	3	36
Expected wellness cases	23.92	48.39	69.59	69.59	16.07	16.93	16.93	62.85
Likelihood wellness	0.44[c]	1.49[d]	0.6[e]	0.6[e]	0.17[e]	0.16[e]	0.16[e]	0.45[e]
Log likelihood ratio	8.504	9.793	11.386	11.386	10.787	11.756	11.756	13.890
Second cluster								
Radius, km	0.94	2.79	7.93	7.93	2.55	2.55	2.55	1.64
Population	13	104	89	89	43	43	43	59
Wellness cases	13	37	67	67	26	26	26	3
Expected wellness cases	7.07	56.54	48.39	48.39	12.34	12.34	12.34	16.93
Likelihood wellness	1.88	0.61[d]	1.49[d]	1.49[d]	2.32[d]	2.32[d]	2.32[d]	0.16[e]
Log likelihood ratio	8.052	9.109	9.793	9.793	10.247	10.247	10.247	11.756
Third cluster								
Radius, km	0.63	0.94	2.79	2.79	1.45	0.12	0.12	2.55
Population	54	13	104	104	44	7	7	43
Wellness cases	42	13	37	37	2	7	7	26
Expected wellness cases	29.36	7.07	56.54	56.54	12.63	2.01	2.01	12.34
Likelihood wellness	1.5	1.88	0.61[d]	0.61[d]	0.15[d]	3.6[c]	3.6[c]	2.32[d]
Log likelihood ratio	7.039	8.052	9.109	9.109	9.094	8.849	8.849	10.248

[a]The maximum spatial scanning window size was at all times 40% (n = 203) of the total population in the entire area (n = 508). The maximum reported cluster sizes represent n = 51, 102, 152, and 203, ie, 10%, 20%, 30%, and 40% of the total population, respectively. Radius in km is the cluster size, population is the number of all respondents within a cluster, wellness cases are those respondents classified as exhibiting mental health or general wellness, and expected cases are those cases that would be expected given the population within a cluster. For a higher likelihood of wellness to be clustered, the measure would convey a value above 1, whereas a value below 1 would be indicative for a lower likelihood wellness cluster.

[b]Percentage of total population in maximum reported cluster size.

[c-e]Significance: [c]$P<0.1$, [d]$P<0.05$, [e]$P<0.01$.

PTSD [marginal] and predisaster probable major depression), reported hurricane-related stressors (loss of sentimental possessions or pets, financial loss), or had stronger peri-event emotional reactions. In contrast, respondents were significantly more likely to exhibit mental heath wellness when they had higher collective efficacy in their neighborhood (Table 3).

Race/ethnicity, predisaster trauma exposure, hurricane-related trauma, and 2 hurricane-related stressors (without any resources for more than 1 week, displaced from home) were not significantly associated with either outcome and were thus excluded in the model selection process. Furthermore, increased demands or relationship problems and social support were excluded for mental health wellness, and male gender and any personal property loss were excluded for general wellness.

Geographic Variation in Associations Between Explanatory Variables and Wellness Outcomes

We found variation in associations between predictors and wellness outcomes across all bandwidths used. Given that model performance was best when considering 30% of the population as the maximum bandwidth (n = 152), and patterns were the same for other bandwidths, we report these results exclusively (Tables 4 and 5). GWR results that accounted for a maximum bandwidth of 20% and 40% of the population can be found in the tables in the **online data supplement**.

For a maximum bandwidth of 30% of the population, we found that age (35–54 years) and predisaster probable PTSD were locally varying predictors and were negatively associated with mental health wellness (Table 4). Respondents exhibiting these characteristics were less likely to show mental health wellness when they lived close to or within Galveston City (Figure 1D-E).

Furthermore, we found that age (age 35–54 years or 55 years or older) and increased demands or relationship problems were locally varying predictors and negatively associated with general wellness (Table 5). Respondents exhibiting these characteristics were less likely to show general wellness when they lived close to or within Galveston City (Figure 3A-C). Additionally, respondents in Galveston City who lived in a neighborhood with higher collective efficacy had a higher likelihood of exhibiting general wellness (Figure 3D).

TABLE 3

Multivariable Regression Results for Mental Health and General Wellness[a]

Predictor	Mental Health Wellness, OR (95% CI)	General Wellness, OR (95% CI)
Age 18–34 years	Ref.	Ref.
Age 35–54 years	0.668 (0.380, 1.163)	0.663 (0.371, 1.179)
Age 55 years or older	0.364[e] (0.200, 0.647)	0.269[e] (0.145, 0.489)
Male gender	1.353 (0.891, 2.058)	–
Less than high school	Ref.	Ref.
High school degree or equivalent	0.434[c] (0.203, 0.914)	0.672 (0.292, 1.564)
More than high school degree	0.922 (0.464, 1.809)	1.269 (0.611, 2.715)
Predisaster probable PTSD	0.550[b] (0.269, 1.102)	0.529 (0.204, 1.250)
Predisaster probable major depression	0.435[d] (0.258, 0.728)	0.345[d] (0.175, 0.649)
Any personal property loss	0.618 (0.315, 1.171)	–
Any loss of sentimental possessions or pets	0.585[c] (0.366, 0.932)	0.328[e] (0.174, 0.593)
Financial loss as a result of Ike	0.454[e] (0.287, 0.714)	0.514[c] (0.298, 0.867)
Increased demands or relationship problems	–	0.588[c] (0.347, 0.986)
Low peri-event emotional reactions	Ref.	Ref.
Medium peri-event emotional reactions	0.392[e] (0.232, 0.657)	0.459[d] (0.254, 0.809)
High peri-event emotional reactions	0.192[e] (0.104, 0.342)	0.213[e] (0.087, 0.462)
Social support	–	0.745 (0.521, 1.060)
Collective efficacy	1.413[c] (1.083, 1.852)	1.379[c] (1.014, 1.896)
Hosmer and Lemeshow's R^2	0.203	0.206

[a]Abbreviations: CI, confidence interval; OR, odds ratio; PTSD, post-traumatic stress disorder; Ref, reference level.
[b-e]Significance codes: [b]$P<0.1$, [c]$P<0.05$, [d]$P<0.01$, [e]$P<0.001$.

TABLE 4

Local Variation in Predictors for Mental Health Wellness, With n = 152, ie, 30% of the Population Used as Bandwidth[a]

	Fixed Terms			Locally Varying Terms					
Predictor	Est.	SE	Z	MIN	LQ	MD	UQ	MAX	STD
Intercept				–0.313	–0.213	0.215	0.418	0.455	0.282
Age 35–54 years				–0.621	–0.551	–0.300	–0.110	0.024	0.213
Age 55 years or older	–0.556	0.153	–3.626						
Male gender	0.141	0.107	1.327						
High school degree or equivalent	–0.383	0.159	–2.404						
More than high school degree	–0.087	0.164	–0.530						
Predisaster probable PTSD				–0.627	–0.544	–0.233	–0.190	–0.054	0.187
Predisaster probable major depression	–0.395	0.114	–3.452						
Any personal property loss	–0.174	0.116	–1.495						
Any loss of sentimental possessions or pets	–0.139	0.118	–1.171						
Financial loss as a result of Ike	–0.339	0.111	–3.064						
Medium peri-event emotional reactions	–0.381	0.110	–3.460						
High peri-event emotional reactions	–0.660	0.121	–5.444						
Collective efficacy	0.272	0.113	2.404						
Pseudo R^2	0.226								

[a]Abbreviations: PTSD, post-traumatic stress disorder. Est., SE, and Z are the regression coefficient estimates, standard errors, and z-values, respectively. MIN, LQ, MD, UQ, MAX, and STD are minimum values, lower quartiles, median, upper quartiles, maximum values, and standard deviations of locally varying regression coefficient estimates across all locations, respectively.

DISCUSSION

In this study, we demonstrated how spatial analysis could be used to identify geographic areas, as well as individuals within such areas, at risk of adversity over time in the aftermath of disaster. We did this by investigating geographic variability of mental health wellness (membership in a resilient trajectory across multiple mental health conditions) and general wellness (membership in a resilient trajectory across mental health, physical health, and role functioning domains). Spatial clusters of high likelihood of mental health and general wellness were located in areas north of Texas City in the hinterland, and spatial concentrations of low likelihood of wellness were exclusively found on Galveston Island facing the Gulf of Mexico.

In the full sample, predictors for lower likelihood of mental health wellness were age 55 years or older, a high school

TABLE 5

Local Variation in Predictors for General Wellness, With n = 152, ie, 30% of the Population Used as Bandwidth[a]

	Fixed Terms			Locally Varying Terms					
Variable name	**Est.**	**SE**	**Z**	**MIN**	**LQ**	**MD**	**UQ**	**MAX**	**STD**
Intercept				–1.983	–1.788	–1.274	–1.162	–1.018	0.320
Age 35–54 years				–0.747	–0.592	–0.200	0.002	0.042	0.275
Age 55 years or older				–1.276	–1.079	–0.722	–0.421	–0.330	0.317
High school degree or equivalent	–0.191	0.182	–1.045						
More than high school degree	0.125	0.186	0.675						
Predisaster probable PTSD	–0.227	0.160	–1.422						
Predisaster probable major depression	–0.499	0.147	–3.386						
Any loss of sentimental possessions or pets	–0.440	0.160	–2.751						
Financial loss as a result of Ike	–0.312	0.135	–2.319						
Increased demands or relationship problems				–0.988	–0.798	–0.324	–0.221	–0.159	0.298
Medium peri-event emotional reactions	–0.349	0.125	–2.798						
High peri-event emotional reactions	–0.670	0.177	–3.781						
Social support	–0.149	0.135	–1.105						
Collective efficacy				0.130	0.226	0.275	0.506	0.781	0.188
Pseudo R^2	0.239								

[a]Abbreviations: PTSD, post-traumatic stress disorder. Est., SE, and Z are the regression coefficient estimates, standard errors, and z-values, respectively. MIN, LQ, MD, UQ, MAX, and STD are minimum values, lower quartiles, median, upper quartiles, maximum values, and standard deviations of locally varying regression coefficient estimates across all locations, respectively.

degree or equivalent, predisaster probable major depression, any loss of sentimental possessions or pets, financial loss as a result of Hurricane Ike, and medium and high peri-event emotional reactions. For low likelihood general wellness, the same was true except for high school degree or equivalent, which was not significant, and for increased demands or relationship problems, which was a significant predictor. Collective efficacy in the neighborhood was a predictor for higher likelihood of both forms of wellness outcomes.

We also found geographic variation in predictors of a lower likelihood of mental health wellness (age 35–54 years, predisaster probable PTSD) and general wellness (age 35–54 years, age 55 and older, increased demands and relationship problems), and negative associations between these predictors and both forms of wellness were stronger with increasing spatial proximity of respondents to Galveston City on Galveston Island. For collective efficacy, the opposite was true, that is, positive associations were stronger with increasing spatial proximity to the city center of Galveston.

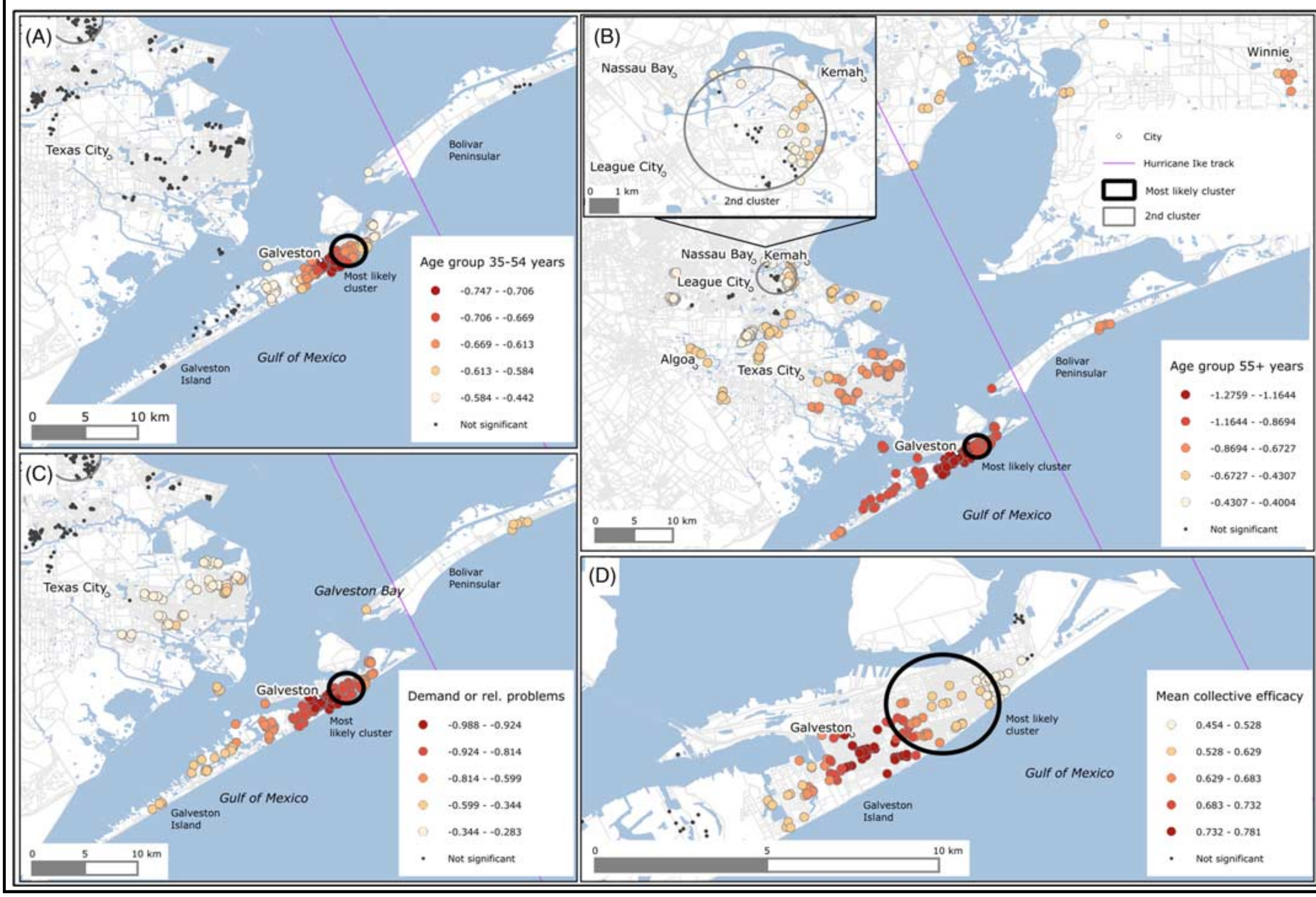
In contrast to prior research that used cross-sectional designs, our outcomes were based on longitudinal trajectories of multiple indicators of mental health as well as indicators of other domains (physical health and role functioning). Hence, the identified geographic variability in this study provides novel evidence that trajectories in resilience across multiple outcomes—ie, postdisaster wellness—may be shaped in part by factors specific to the geographic location. Such factors could include the community-wide exposure to the disaster (eg, flooding, wind speed) or other community characteristics (eg, economic development, housing quality, social capital).

We found spatial clusters of low likelihood of mental health and general wellness indicating geographic concentrations of increased risk on Galveston Island. This increased risk might have evolved because of a greater exposure to hurricane winds and storm surge flooding (see Figure 1). Prior research from a variety of contexts has documented that higher dose effects, for example, due to geographical proximity to the disaster, can contribute to increased postdisaster psychopathology.[11,12,45] Hurricane Ike made landfall over the east end of Galveston Island crossing the Bolivar Peninsula, which together with the west side of Galveston Bay experienced storm surge levels of 3 to 4 meters, inundating large parts of the coastal areas.[46] Increased exposures at these locations along with the enduring calamities in the aftermath of the disaster may have amplified dose gradients that consequently led to the geographic concentration of lower likelihood of mental health and general wellness on Galveston Island and Galveston City, for which we provided evidence. In turn, we noted spatial concentrations of high likelihood mental health and general wellness in the hinterland north of Texas City, which may be due to attenuated individual and socioecological risk and amplified health-promoting factors prominent in this area as compared to the other areas. This relationship warrants further investigation in subsequent studies.

Consistent with a prior study,[9] we found differences in predictors of mental health versus general wellness. In addition, we found differences in these predictors across geographic spaces and locations. The strength of associations for middle age (35–54 years) and predisaster probable PTSD varied geographically for mental health wellness, and the strength of

FIGURE 3

General Wellness Clusters and Predictors. (A) Spatial heterogeneity of the geographically varying predictor age group 35 to 54 years and spatial clusters of low likelihood general wellness. (B) Spatial heterogeneity of the geographically varying predictor age group 55 years and above and spatial clusters of low likelihood general wellness. (C) Spatial heterogeneity of the geographically varying predictor demand or relationship problems and spatial clusters of low likelihood general wellness. (D) Spatial heterogeneity of the geographically varying predictor mean collective efficacy and spatial clusters of low likelihood general wellness. Note: $N = 152$, ie, 30% of the total sample population was used as the spatial neighborhood definition. Shaded points in (A) to (D) represent the strength of significant regression coefficients associated with general wellness at each respondent's location. Source: National Hurricane Center[14] and authors' own survey. Note that respondents' locations have been altered to preserve confidentiality.



associations for middle and older age (age 35–54 years or 55 years or older) and increased demands or relationship problems varied geographically for general wellness. These predictors were associated with a lower likelihood of mental health and general wellness most pronounced in Galveston Island.

One reason middle or older age might show stronger associations with both forms of wellness in Galveston Island is that it might be more predictive in areas with high levels of exposure. Older age has been identified as a both protective factor[47] and a risk factor[9,48,49] for adverse postdisaster psychological outcomes in prior research. Here we have provided evidence that the inverse relationship between middle age and mental health wellness as well as middle and older age and general wellness increased in strength with proximity to the areas where the hurricane hit hardest. Similarly, predisaster probable PTSD and increased demands and relationship problems might be barriers to wellness, particularly in the context of high community-level exposure.

In turn, neighborhood community collective efficacy, that is, the perception of mutual trust and willingness to help each other, was exclusively predictive of general wellness in Galveston City, with increased associations towards the city center. There are 2 possible explanations for this finding. First, the health-promoting nature of neighborhood collective efficacy documented elsewhere[50,51] might be of special importance in the context of high community-level exposure.

Second, other distinguishing characteristics of Galveston City compared to other geographic areas in the study region may have provided more opportunities for social interaction. In this vein, Cohen et al[52] suggested that certain features of the built environment may set the stage for neighborhood social interactions, thus serving as a foundation for underlying health and well-being. It is possible that the city provided a different social fabric within its neighborhoods as compared to suburban areas in the hinterland in terms of neighborhood walkability, enabling more social contacts, which eventually helped strengthen collective efficacy.

Limitations

This study had some limitations. First, the study took place in Galveston and Chambers counties in the aftermath of Hurricane Ike and the findings may not be generalizable to other geographic areas in the aftermath of other disasters. Second, our study had a rather low response rate and there might have been systematic differences between responders and nonresponders. Furthermore, there was variation in response rates across the 5 sampling strata that may have influenced the findings. However, it is worth noting that there were no differences between the study sample and the population in the sampling frame of Galveston and Chambers counties,[18] mitigating this concern. Third, although our sampling methodology aimed to recruit a representative sample, we used an unweighted population sample owing to methodological restrictions. Furthermore, oversampling was performed in those areas close to the shoreline, so that there still might be differences between characteristics of the sample and the larger population living within Galveston and Chambers counties, further limiting the generalizability of the results. Fourth, we included all participants, even if they did not experience hurricane-related stressors and traumatic events. In the analysis, those participants may have been classified as "resilient," despite not having experienced these events. This is at odds with theoretical frameworks that require exposure to significant risks for a person to be classified as resilient.[53] However, we opted to use the full sample to better represent both the study area and the broader range of persons who experience disasters, including those who were not exposed to stressors and traumatic events. Fifth, the sample size limited statistical power and prevented geographic analysis taking into account more fine-grained spatial variations. Sixth, mental health and general wellness were defined on the basis of a limited set of postdisaster conditions. Further studies would include additional conditions, including other common postdisaster mental health problems (eg, generalized anxiety, substance abuse) and specific physical health complaints (eg, headaches, digestive problems).

CONCLUSIONS

Despite these limitations, this study provided additional evidence that postdisaster mental health and general wellness are shaped by disaster-related exposures as well as by individual-level and socioecological factors. Moreover, these results suggest that predictors for mental health and general wellness may manifest differently across geographic space depending on spatial concentrations of higher versus lower likelihood of wellness and different levels of community exposure. A spatial epidemiologic analysis therefore may help to identify geographic areas and individuals within them less likely to experience wellness. Future spatial analyses could be strengthened by efforts to ensure that the disaster-affected population is adequately represented in statistical models, including geographic sampling that better reflects the population of different areas and the use of statistical weighting in spatial statistical applications. Other forms of georeferenced data such as land cover could be used to identify physical hazards. Mental health service locations could be included in statistical models to investigate regional disparities and gaps in mental health needs and services. Therefore, it is desirable that interdisciplinary research teams, drawing on, for example, expertise in psychology, epidemiology, geography, or service administration, efficiently collaborate. Further applications of this approach have great potential to inform public health interventions that focus on high-risk populations in specific locations before a disaster. After natural disasters and other catastrophic events, this approach may help to identify those subpopulations in specific areas that have greatest need. The approach could be transferred to other areas to advance preparedness and population wellness in similar contexts worldwide.

About the Authors

Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, New York (Drs Gruebner, Cerdá, and Lowe, Ms Joshi); Department of Epidemiology and Biostatistics, School of Public Health, University at Albany, State University of New York, Albany, New York (Dr Tracy); Geisel School of Medicine at Dartmouth, Hanover, New Hampshire (Dr Norris); and School of Public Health, Boston University, Boston, Massachusetts (Dr Galea).

Correspondence and reprint requests to Oliver Gruebner, Columbia University, Mailman School of Public Health, Department of Epidemiology, 722 West 168th Street, New York, NY (e-mail: gruebner@hsph.harvard.edu).

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SUPPLEMENTARY MATERIAL

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