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Adjustments of Socially Vulnerable Populations in Galveston County, Texas USA Following Hurricane Ike

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Abstract: The role of socio-demographic vulnerability to hazards is an increasingly important aspect for consideration in disaster mitigation and adaptation. This paper examines the spatial adjustments of populations to the 2008 Hurricane Ike by estimating the effects of damage on the changes of socially vulnerable populations pre- and post-Hurricane Ike. Multivariate regression models are used to understand household-level adjustments in different flood zones and inundation levels at the block-group level in Galveston county. In contrast to past literature that suggests that vulnerable populations remain or move into hazardous areas post-disaster, our results indicate that socially vulnerable populations have moved out of highly damaged areas. The tremendous investment opportunity post-disaster and the slow distribution of funds to recover public housing on Galveston Island provide potential explanation of the estimated adjustment patterns. Analyzing post disaster adjustments offers important insights into the "resilient" recovery of Galveston County post-Hurricane Ike. Our results also point to potential vulnerabilities that may arise in the future because of the change in community identity and the loss of social memory. Understanding disaster-driven changes in community make-up will help inform potential recovery trajectories from future catastrophes.

Keywords: disaster vulnerability; spatial and temporal adjustments; hurricane Ike; social vulnerability index

1. Introduction

Floods are the most persistent and costly hazards that impact almost all parts of the United States [1], and are expected to become more frequent and damaging with the on-going climate change and resultant sea level rise [2]. Their threats are particularly felt in low-lying coastal areas, where a large number of the population resides, and some of the most valuable economic assets are at risk [3]. Despite growing exposure, the brunt of flood disasters is disproportionately felt by socially vulnerable populations because they lack resources to readily adapt to and absorb disturbances [4–7]. Evidence also suggests that socioeconomically disadvantaged groups are more prone to the effects of flooding because of the depressed housing market in flood prone areas [8–10]. Poor institutions (both the social and public) could further erode disadvantaged population's adaptive capacity, posing major impediments to quick recovery [11–13]. Understanding the drivers of disaster vulnerability and adaptive capacity of vulnerable segments of the population has become imperative in identifying the challenges of disaster adaptation. The better understanding of these drivers will also inform public policy pertinent to future disaster management and planning.

In this paper, we examine the spatial and temporal adjustment patterns to the destruction wrought by the 2008 Hurricane Ike among vulnerable segments of the population residing in Galveston County, Texas. Our overall results indicate significant decline in social vulnerability (across various indexed measures) in hazard-prone block groups. While the decline in overall social vulnerability is suggestive of resilient recovery, such major changes may also indicate an overall change in community identity. The loss of population with long-established roots in coastal communities means the social memory of these groups may also be lost [14,15]. The loss of social memory and human networks from hazard displacement may in turn degrade the ability for a community, and its institutions, to systematically draw from past lessons [16]. Further, there are many measures, that vary across geographies and catastrophes, both quantitative and qualitative, economic, and ecological that can be used to measure a place's vulnerability and resilience [17–19].

Our paper builds on and extends the past literature by integrating social vulnerability indices and various methodological approaches to the hazard of place model developed by [20]. Utilizing the social vulnerability model to examine the adjustment of populations provides a link between the bodies of work on social vulnerability and household adjustments to disasters [21,22]. Another important contribution is the consideration of spatial effects in disaster adjustments, which is an important and often overlooked methodological aspect in adjustment studies.

The rest of the paper is organized as follows. In Section 2, we review literature related to disaster vulnerability and household adjustments. Section 3 provides the background context for the study area. Sections 4 and 5 describe data and methods, respectively. In Section 6, results are presented, which are discussed in the last section, Section 7.

2. Literature Review

2.1. Social Vulnerability

The wealth of past research has provided a definition of vulnerability in the context of hazards [23], and the general consensus is that hazard vulnerability is the state that exists within a system before a physical hazard happens, along with the communities' ability to cope with hazards once they occur [24]. Social vulnerability is the social component (i.e., income, age, etc.) of hazard vulnerability, which amplifies the likelihood of negative outcomes [25]. Attributes of social vulnerability include the lack of access to resources, limited access to political power and lack of political representation, lack of social capital, poor building stock including structural soundness and occupancy density, and age [4,12,20,23,26–30]. Marginalized groups (e.g., ethnic minorities, poor, unemployed) are often considered to be particularly vulnerable to disasters because they lack financial resources to buffer against the consequences of a disaster as well as prepare for (e.g., purchase hazard insurance, afford hazard-proof housing) and recover after the disaster [29,31–33]. Inequities for these groups are typically social, political, and economic [29,31,32]. The consequences of these inequalities are especially evident in housing, which is usually more densely occupied, less structurally sound, and in hazard-prone areas [29,31,32].

Social vulnerability is also felt across the age divide, and in particular, elderly and children are considered to be the most vulnerable groups in disaster events. The latter lack the ability to protect themselves because of lack of resources and information, while the former may live on fixed incomes and may have health problems effecting their cognitive and physical abilities to prepare for and respond to disastrous events [23,27,29,34–39]. This paper draws upon these measures of social vulnerability to explore adjustments of households considered the most vulnerable in terms of housing, income, age, and race/ethnicity.

2.2. Household Adjustments

Following disasters, there are often large dislocations of populations, and examining the adjustments and drivers of adjustment is important for delineating future vulnerability and informing effective disaster recovery policy [21,22,33,40–42]. The ways in which households adjust and respond to disasters largely depend on their entitlements and assets, financial capacity, access to political power, risk perception, and social capital [23,27]. The latter often refers to the networking, cultural and societal norms, and trust within social and economic activities [43].

Extant research highlights a few options for disaster adjustments including moving out of harm's way, self-protection, and self-insurance [21,22]. Availability of financial resources often determines adjustment patterns, and the lack of them represents impediment to recovery for many, in particular for those economically disadvantaged. For example, wealthier people may choose to return back and rebuild after disaster because they can afford rebuilding [22]. Importantly, they return because they are able to self-protect (e.g., retrofitting homes) and insure [44]. Low income households may also remain in damaged areas because of lack of resources to relocate and a depressed housing market post-disaster [22]. The lack of resources also implies that this segment of the population is less likely to retrofit or hazard-proof homes, or self-insure, and it is expected that dwellings for poor populations will remain vulnerable to future hazard events [20,29,33].

Governmental assistance and other financial resources following disasters can also play a vital role is disaster adjustment [21,45]. Research indicates that public disaster aid can create perverse incentives by dissuading private individuals from undertaking self-protection/self-insurance measures in anticipation of disaster aid [46]. For example, Kousky et al., (2018) found that federal disaster grants given to individuals reduces flood insurance coverage [45]. Davlasheridze and Miao (2019) also suggest reduced insurance policies in response to increased Public Assistance (PA) grants, specifically those that target public infrastructure and rehabilitation programs [46]. Two possible explanations for such responses are important to highlight. First, the PA grants could signal federal disaster bail-out and may discourage private risk management (in a similar manner as the direct cash assistance). Second, public projects could alter the risk perception of individuals (e.g., people may feel secure after large public investment in flood protection infrastructure). Public projects targeting infrastructure recovery can incentivize homeowners to stay in high risk areas and businesses to reopen [21,31,47–50].

Public projects, specifically home buyouts, often initiated after a major disaster, seek to permanently relocate housing away from hazardous areas, force relocation, and can also reduce hazard vulnerability [51]. However, residents living in communities that rely heavily on property tax revenues to finance local service delivery have more flood protective infrastructure (e.g., levees), and coastal areas with shoreline amenities were less likely to participate in home buyouts [52].

While it is not commonly recognized in research, social memory of communities, which refers to the shared experiences of social groups, also plays a role in how households respond to natural disasters [14,15]. The social memory is important because it helps people understand how to respond (evacuate or stay), cope (adjust to the situation before and after), and recover based on the lessons learned from past disturbances [16,53]. These memories, when shared through social learning processes, play a critical role for the rebuilding and reorganization phase post-disaster [54]. Lidscog (2018) showed that after a large wildfire incident in 2014, the Swedish community has recovered to be possibly more resilient and prepared for future disasters. The author underscores the increased social mobilization and social engagement as primary defining factors of resilient recovery [55]. Moreover, community engagement has the potential capacity to reduce vulnerabilities through bottom up adaptation strategies, specifically establishing community-based adaptation committees (CBACs), which bridge the gap between affected communities and government agencies [56,57].

However, post disaster household adjustments can lead to further social isolation of vulnerable group. Scholars address systematic social isolation commonly associated with American ghettos [58]. By living in segregated neighborhoods, residents are limited in their access to resources, ability to escape poverty, and job opportunities [59]. This is specifically apparent for minorities living in the inner city [60]. The effects of urban poverty and social isolation became hypervivid in the context of natural disasters in 2005 when hurricane Katrina devastated New Orleans [61,62]. One of the leading causes of urban poverty has been linked to the spatial concentration of mono tenure estates [58,63]. There has been a significant research and public focus on social mixing and revitalization policies, both urban and rural. (The HOPE VI program is one such program implemented by the U.S. Department of Housing and Urban Development with the aim to replace inner city public housing structures with integrated subsidized communities (Elliott et al., 2004; National Commission on Severely Distressed Public Housing, 1992; Elliott et al., 2006) [32,64].) Disasters provide the opportunity to revitalize marginalized neighborhoods by rebuilding with mixed tenure communities. This is important in the context of disasters because social organization can increase community's adaptive capacity [30,56,57,65]. However, the widespread demolition of public housing in an effort to revitalize urban areas has often led to the replacement of tenure as opposed to tenure mixing, where low mono-tenure estates are consequently taken over by middle mono-tenure estates, as well as the displacement of low income populations [66–69]. It is important to also note that gentrification does not solely occur based on urban policy. "Outsiders" could take advantage of low-cost housing post-disaster as investment opportunities. This is currently the challenge faced by Port Aransas, Texas, which was devastated by Hurricane Harvey in August of 2017. There has been a large influx of investors to this small coastal community threatening to change its identity [70]. The influx not only threatens to reshape community identity, it can also degrade social memory of communities, and lessen the communities' adaptive capacity to risk.

Building on these two lines of research, this paper examines adjustment patterns across socially vulnerable groups of the population in Galveston County in response to Hurricane Ike. Throughout, the maintained assumption is that socially vulnerable populations will be more geographically concentrated in high risk and high damage areas following a disaster incident because of their inability to leave or rebuild, opportunistic adjustments in housing markets, and partially due to potential perverse incentives associated with disaster assistance programs.

3. Study Area

Our study area covers Galveston County, located on the upper Texas Gulf Coast about 25 miles south of Houston. It is a large metropolitan area encompassing the Galveston Bay, East Bay, and West Bay (see Figure 1). The South Eastern Gulf of Mexico is one of the most Hurricane- and flood-prone areas in the United States, and on average experiences a major Hurricane once every 15 years [71]. Due to rising sea levels, the National Oceanic and Atmospheric Administration (NOAA) predicts that the frequency of surge events in this region may increase dramatically and could become as frequent 200 days a year, with 80 to 100% attributed to higher tides [72].

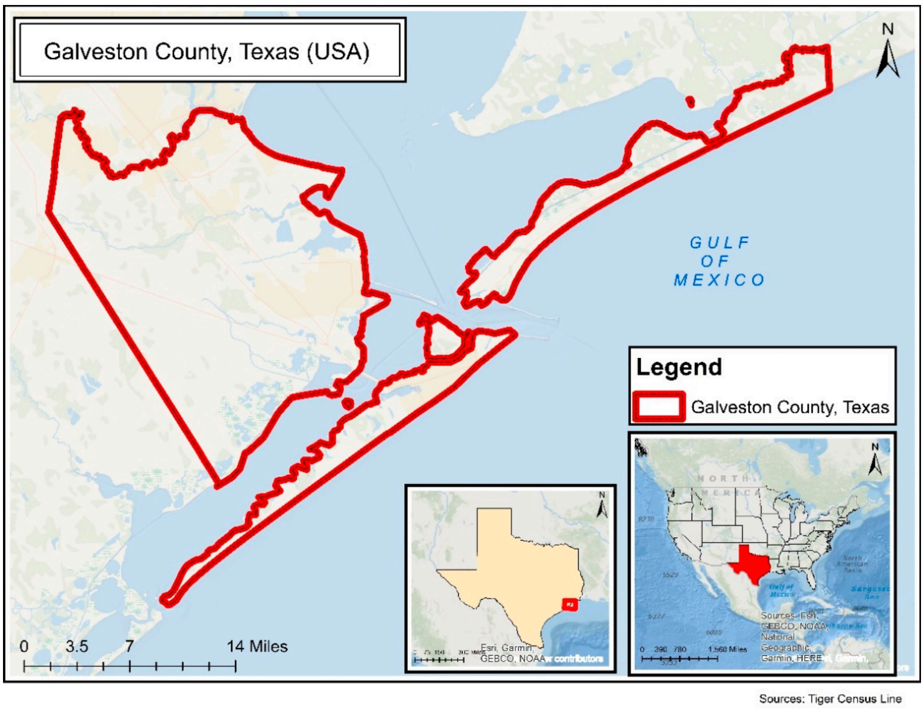

Figure 1. Study Area (Galveston County). Notes: The figure outlines the location of Galveston County in the state of Texas, USA. Datum: NAD 1983, Projection/Coordinate System: UTM Zone 14N.

A large portion of Galveston County is Galveston Island, a low lying micro tidal barrier island. One of the unique features of Galveston Island is the seawall built in response to the 1900 storm, the deadliest ever recorded Hurricane in U.S. history, responsible for approximately 8000 fatalities. Despite significant structural mitigation efforts, (Other large infrastructure project targeting flood mitigation in the Galveston County include a large levee system in Texas city, built in response to Hurricane Carla in 1961 to protect some of the valuable industrial assets such oil refineries.) this area continues to be overwhelmed by coastal storms and hurricanes. Hurricane Ike (2008) was a recent category 2 storm that brought a surge level comparable to a category 5 hurricane and caused massive property damage [73,74]. In this research we focus on the impacts of Hurricane Ike, as it gives enough time post-2008 to explore the long-term responses of vulnerable populations to its catastrophic devastation.

4. Data

Data for this study came from various sources including the American Community Survey of U.S. Census Bureau, The Harris County Flood Control District, and The Federal Emergency Management Agency (FEMA). Socio-economic and demographic block group level data for Galveston County for the years 2000 and 2015 were drawn from the Census American Community Survey [75,76]. We specifically focus on variables measuring various attributes of social vulnerability. These include the race and ethnicity, people in poverty, female population, female-headed households, number of renters, population with no vehicle, population under 5 years old and 65 years and older, unemployed population, number receiving social security income, number of population without a high school diploma, and population living in mobile homes. The population counts were converted into percentages, and the changes in percentages over the two periods were calculated at a block group level. There were changes in block group lines from 2000 to 2015. Specifically, there were 211 block groups in 2000 and only 194 block groups in 2015. Only block groups that were matched between the two periods were considered for analysis (n = 152). These data were chosen based on the "Social Vulnerability Concepts and Metrics" Table 1 in Cutter et al. (2003, pp. 246–249) [20]. Appendix A Table A3 shows the concept and the variable used to measure various concepts. While there are many other factors that contribute to a person or households' vulnerability (e.g., Rural/Urban, Special Needs Populations), the data measuring them were not readily available at the block group level for both years.

Hurricane Ike's inundation level data were obtained from The Harris County Flood Control District [77]. The data were spatially joined with the Block group shapefile in order to analyze average inundation levels by block group. Five levels of inundation were created, including (1) less than 2 ft; (2) 2–4 ft; (3) 4–6 ft; (4) 6–8 ft; and (5) 8–10 ft. Categorizing inundation at different levels is intended to capture the varying degrees of damage on changes in socio-economic characteristics of households across block groups and over-time.

Flood zone areas were drawn from the FEMA [78]. Flood zone data was spatially joined with block group data, and the percentage areas for each of the flood zone classes were calculated for each block group. For this research, three different flood risk zones were used: A-zones, X-zones, and V-zones. A-zones represent areas with a 1% annual chance of flooding in the 100-year flood plain, V-zones represent coastal areas in the 100-year flood plain with a 1% annual chance of flooding and coastal velocity hazard, and X-zones represent moderate to low risk areas outside of the 1% and 0.2% chance of annual flooding outside of the 500 year floodplain [78]. Flood zones in the model capture the existing "objective" risk for flooding.

The summary statistics for model variables are reported in Table 1. Appendix A Tables A1 and A2 report summary statistics of level variables corresponding to years 2000 and 2015, respectively.

Table 1. Summary Statistics of Variables that Capture Social Vulnerability.

Variable	Description	Mean	Std. Dev.	Min	Max
Dpctpoverty	Δ in the % of the population in Poverty	−5.38	13.60	−44.64	38.80
Lpctpoverty	% of the population in Poverty	27.69	15.32	1.35	72.96
Dpctheadfem	Δ in the % of the population in with a Female Headed Household	−29.65	17.33	−78.96	9.99
Lpctheadfem	% of the population in with a Female Headed Household	45.64	16.72	10.65	84.39
Dpercentnov	Δ in the percent of the population with no vehicle	−0.75	9.86	−50.57	33.94
Lpercentnov	% of the population with no vehicle	10.60	11.35	0.00	62.55
Dpctunemplo	Δ in the % of the population unemployed	1.10	5.45	−20.55	19.22
Lpctunemplo	% of the population unemployed	4.69	3.49	0.00	20.55
Dpctsocials	Δ in the %t of the population recieving Social Security	4.75	12.35	−28.58	44.23
Lpctsocials	% of the population recieving Social	26.41	10.93	3.90	63.10
Dpercentren	Δ in the % of the population renting housing	2.98	14.11	−32.65	41.29
Lpercentren	% of the population renting housing	37.41	22.27	1.22	89.48
Dpctmobile	Δ in the % of the population living in Mobile Homes	−0.72	5.83	−20.67	21.28
Lpctmobile	% of the population living in Mobile Homes	5.83	10.72	0.00	53.63
Dpctnotwhite	Δ in the % of the population that is not White	5.31	18.01	−44.81	53.09
Lpctnotwhite	% of the population that is not White	43.17	26.20	3.62	100.00
Dpctyoung	Δ in the % of the population 5 years old and under	−1.83	5.23	−17.08	14.45
Lpctyoung	% of the population 5 years old and under	7.66	3.29	0.00	17.08
Dpctold	Δ in the % of the population 65 years old and over	1.66	7.73	−14.10	34.82
Lpctold	% of the population 65 years old and over	13.30	6.81	2.28	43.44
Dpctfemale	Δ in the % of the population that is female	0.33	7.35	−33.02	20.78
Lpctfemale	% of the population that is female	51.02	4.72	27.30	59.94
Dpctunder12	Δ in the % of the population with less than a 12th grade education	−5.84	11.69	−39.53	31.13
Lpctunder12	% of the population with less than a 12th grade education	23.08	12.31	0.00	54.01
DSV	Δ in Z-scores Social Vulnerability indicies	0.15	1.13	−4.02	2.83
LSV	Z-score of Social Vulnerability index	0.02	0.99	−1.94	2.88
Inundation1	Average inundation is less than or equal to 2 ft	0.26	0.44	0	1
Inundation2	Average inundation is greater than 2 ft but less than or equal to 4 ft	0.27	0.45	0	1
Inundation3	Average inundation is greater than 4 ft but less than or equal to 6 ft	0.25	0.43	0	1
Inundation4	Average inundation is greater than 6ft but less than or equal to 8 ft	0.16	0.37	0	1
Inundation5	Average inundation is greater than 8 ft but less than or equal to 10ft	0.05	0.22	0	1
X-Zone	percentage of the block group in X flood zones	58.18	42.01	0.00	100.00
A-Zone	percentage of the block group in A flood zones	36.02	38.57	0.00	100.00
V-Zone	percentage of the block group in V flood zones	5.79	18.15	0.00	92.02

Notes: The sample contains 152 observations. Variable names starting with D represent the differences in percent between 2015 and 2000; the variable names starting with L correspond to lagged values in 2000. Sources: U.S. Census Bureau, 2000; 2015; American Community Survey, 2000; 2015.

5. Methods

5.1. Principal Component Analysis

To construct social vulnerability indices for each block group, principal component analysis (PCA) was employed. PCA extracts the dominant patterns within a data matrix to create a smaller set of uncorrelated components [79]. To retain the most influential components which described most of the variance within the data, the components were retained based on the Kaiser criterion, i.e., components for which eigen values were greater than or equal to 1.

The variables used in the construction of the Social Vulnerability index (SV) included block group level percentages for female population, female-headed households, renters, population with no vehicle, population under 5 years old, population 65 and older, unemployed population, population receiving social security income, percent with less than a high school degree, and percentage of the population living in mobile homes. Once the components were identified using PCA for each year, the unweighted average of the components was taken to create an SV index where each factor was assumed to have the same contribution to the block group's overall social vulnerability. Positive values of SV indicate higher levels and negative values indicate lower levels of social vulnerability, respectively. Following the approach described in Cutter and Finch (2008), for the social vulnerability indices to be compared between the two years, they were transformed into z-scores [80].

5.2. Estimation

5.2.1. The Ordinary Least Squares (OLS)

The OLS regression model was used to further examine the effect of Hurricane Ike induced inundation on the changes in socioeconomic and demographic makeup of the block groups, as specified in Equation (1):

$$y_{j,2015}^{k} - y_{j,2000}^{k} = \beta_0 + \beta_1\left(y_{j,2000}^{k}\right) + \beta_2 Risk_j + \sum_{j=1}^{5} \gamma_j D_j + e \quad (1)$$

where $y_{j,t}^{k}$ represents the proportion of households (or people) of type k in the census block j in time period t (t corresponds to 2000 and 2015 years). Household type k includes percentage of people under 5 years, percentage of people 65 and older, percentage of renter occupied units, percentage of people in poverty, percentage of female-headed households, percentage of unemployed, percentage of female population, percentage of non-white population, percentage with less than a high school diploma, percentage of mobile homes, percentage people receiving social security, and percentage of people with no vehicle. We further estimate the model in which $y_{j,t}^{k}$ corresponds to SV index for block group j at time t. D_j is the vector for five inundation levels capturing varying degree of impacts of Hurricane Ike, the omitted category is level one inundation (i.e., less than 2 feet). $Risk_j$ is the variable that captures objective risk of flooding, represented by the two types of flood zones (A and V zones). The moderate and no flood risk zones are omitted levels. e is the error term assumed to be normally distributed.

5.2.2. Spatial Regression Model

Spatial autocorrelation violates the assumption of uncorrelated errors in the OLS model. Furthermore, if there is spatial lag in the model the dependent variable y in block group i is affected by the independent variables in both block groups i and j, the assumption of uncorrelated errors is violated again. In such instances, a spatial autoregressive model is most appropriate to account for the autocorrelation in either the error or the lag of the dependent variable.

In order to test for spatial autocorrelation several diagnostics were conducted based on the Lagrange Multiplier test. The two different models, one for lag dependent variable and one for error spatial correlation were estimated. The spatial model that accounts for spatial lag dependency is specified by Equation (2) and the model for spatial error is specified as Equation (3) as follows:

$$y_{j,2015}^{k} - y_{j,2000}^{k} = \beta_0 + \rho W y + \beta_1\left(y_{j,2000}^{k}\right) + \beta_2 Risk_j + \beta_3 D_j + \mu \quad (2)$$

$$y_{j,2015}^{k} - y_{j,2000}^{k} = \beta_0 + \beta_1\left(y_{j,2000}^{k}\right) + \beta_2 Risk_j + \beta_3 D_j + \varepsilon \quad (3)$$

$$\varepsilon = \lambda W \varepsilon + \mu$$

where Wy is the spatially-lagged $y's$ (i.e., $y_{2015}^{k} - y_{2000}^{k}$) and W corresponds to spatial weights matrix. ρ is the coefficient associated with the spatial lag variable. In Equation (3), ε corresponds to a spatially weighted error term, where λ is the autoregressive coefficient, $W\varepsilon$ is the spatial lag for the errors, and μ is another error term.

6. Results

6.1. Social Vulnerability Index

Through the PCA, the twelve variables were condensed into sets of uncorrelated components. For the year 2000, three components were retained based on the Kaiser retention method (Appendix A Figure A1). The components were given general names to describe them, although more individual variables were loaded onto these components (see Table 2). Overall, the three components described 69% of the variation. For the year 2015, six components with eigenvalues greater than one were retained (Appendix A Figure A2). The naming of these components differed from the year 2000, as the loadings on the components were not the same (see Table 3). Overall, the six retained components described 70% of the variation in the year 2015. In Figures 2 and 3, we show the spatial distribution of Social Vulnerability by block group for the years 2000 and 2015, respectively. Positive values for block groups show more vulnerability, and the negative values indicate less vulnerable block groups.

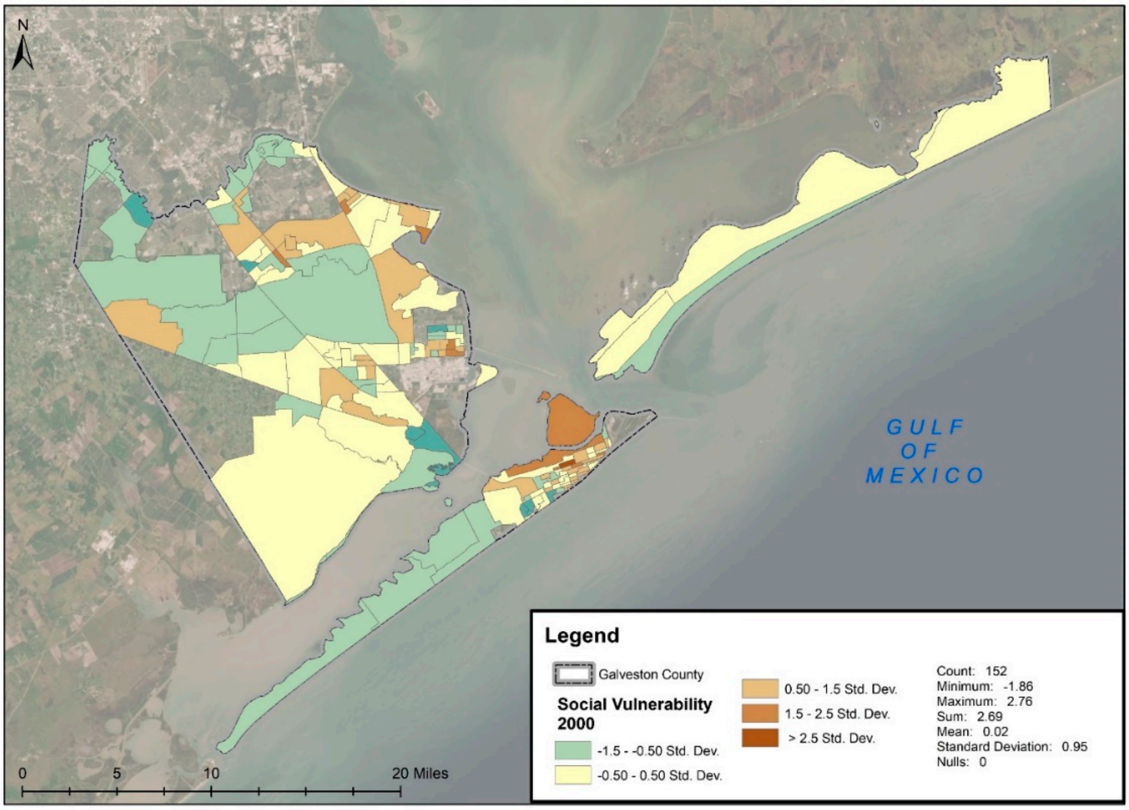

Figure 2. Indexed Social Vulnerability (SV) by Block Group for Galveston County (2000). Datum: NAD 1983, Projection/Coordinate System: UTM Zone 14N.

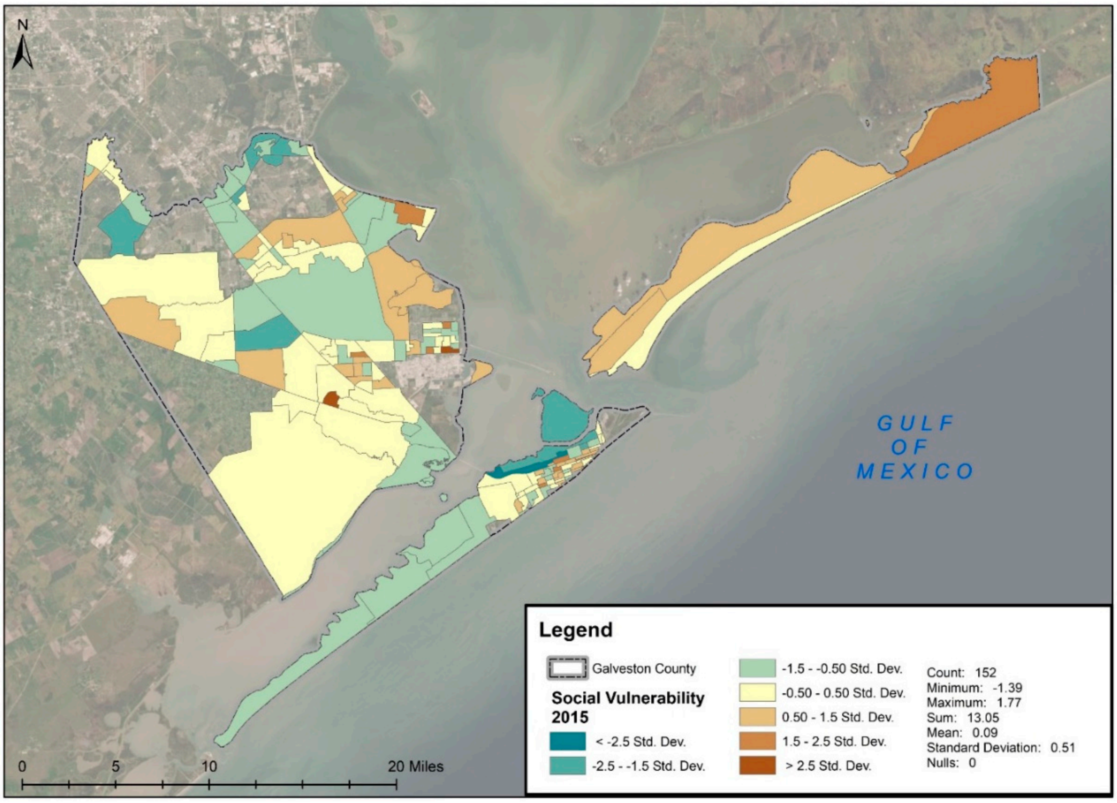

Figure 3. Indexed Social Vulnerability (SV) by Block Group for Galveston County (2015). Datum: NAD 1983, Projection/Coordinate System: UTM Zone 14N.

Table 2. Variable loadings (year 2000).

Factor	Percent Variance Explained	Dominant Variable
Population with limited means	39.74%	% in poverty
Dependent population	18.66%	% 65 years and older
Population in less structurally sound housing	10.66%	% of mobile homes

Notes: The table list variables retained for principal component analysis (PCA) based on Kaiser retention method. Source: The authors.

Table 3. Variable loadings (year 2015).

Factor	Percent Variance Explained	Dominant Variable
Marginalized population	17.14%	% not white
Dependent population	14.95%	% receiving social security income
Less skilled population	10.74%	% with less than a 12th grade education
Population in less structurally sound housing	9.76%	% of mobile homes
Population with a dependent	9.05%	% female headed household
Population with limited financial stability	8.47%	% unemployed

Notes: The table list variables retained for PCA based on Kaiser retention method. Source: The authors.

Components were aggregated for both years by averaging to create a composite index which captures social vulnerability (Appendix A Table A4 provides summary statistics for these SV indices). Z-score transformations were then applied to both years so that they could be compared. Summary Statistics for the Z-scores of SV for 2000 and 2015 are reported in Table 4.

Table 4. Summary statistics for Z-score of SV.

Variable	Mean	Std. Dev	Min	Max
2000 SV	0.02	0.99	−1.94	2.88
2015 SV	0.16	0.98	−2.65	3.38

Source: The authors.

6.2. Regression Results

The series of autoregressive tests indicated that there were six models which violated OLS assumptions (see Appendix A Table A5). Five of the models had autocorrelation in the lag of the dependent variable, and one model exhibited spatial autocorrelation in the error term. Hence, for every OLS model, a corresponding spatial lag model (SLM) or spatial error model (SEM), judged by the spatial autoregressive tests, are presented in the paper.

First, in Table 5 we present regression results from the model in which the difference in SV is used as a dependent variable. As results indicate social vulnerability decreases in a statistically significant manner with higher levels of inundation, specifically for levels 3 (4–6 ft), 4 (6–8 ft), and 5 (8–10 ft) relative to level 1 (0–2 ft) and no significant change was observed in block groups falling under inundation level 2 (2–4 ft) relative to the level 1. The results also show a statistically significant increase of social vulnerability in A-zones, relative to X-zones.

Table 5. Regression results (SV).

	SV
Lag of Social Vulnerability	−0.667 ***
	(0.077)
A-zone	0.009 **
	(0.004)
V-zone	0.015 **
	(0.006)
Inundation level 2	−0.400 *
	(0.21)
Inundation level 3	−0.951 ***
	(0.315)
Inundation level 4	−1.326 ***
	(0.398)
Inundation level 5	−1.619 ***
	(0.522)
R^2	0.39
N	152

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Standard errors in parenthesis. Dependent variable is the difference in SV indices between 2015 and 2000.

To understand what has contributed to a decline in social vulnerability, we report results from various models using different components of vulnerability as our dependent variable. The results for various housing variables are presented in Table 6 and reveal that the percentage of renter occupied housing units decreased in a statistically significant manner in inundation level 3 (i.e., inundation 4–6 ft) areas, relative to inundation level 1. The results for mobile homes show a statistically significant increase in inundation level 3 areas relative to inundation level 1. There are no statistically significant changes in flood zones.

Table 6. Regression for housing vulnerability.

	Percent Renter	Spatial Lag (Percent Renter)	Percent Mobile Homes	Spatial Error (Percent Mobile Homes)
A-zone	0.048	0.049	−0.034	−0.034
	(0.057)	(0.92)	(1.49)	(1.53)
V-zone	−0.039	−0.039	0.024	0.024
	(0.088)	(0.47)	(0.69)	(0.7)
Inundation level 2	−3.248	−5.238 *	−0.369	−0.381
	(3.205)	(1.7)	(0.28)	(0.29)
Inundation level 3	−7.208	−9.698 **	3.208	3.210 *
	(4.831)	(2.1)	(1.65)	(1.69)
Inundation level 4	−2.46	−4.131	2.742	2.742
	(6.095)	(0.72)	(1.11)	(1.14)
Inundation level 5	−2.803	−4.519	−0.119	−0.123
	(8.051)	(0.6)	(0.04)	(0.04)
Lag dependent variable	−0.161 ***	−0.162 ***	−0.156 ***	−0.157 ***
	(0.056)	(3.09)	(3.52)	(3.13)
R^2	0.08	0.073	0.13	0.12
N	152	152	152	152

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000.

Results presented in Table 7 show adjustments of populations by income level. Significant declines, indicated by negative and statistically significant coefficients associated with inundation levels 2, 3, 4, and 5, are found for proportion of population on social security benefits, relative to inundation level 1. Results also reveal a statistically significant decrease in percent unemployed for inundation level 3 relative to level 1. Damage coefficients for percent poverty show a statistically significant decrease in inundation levels 2 and 3, relative to level 1. Results indicate a statistically significant increase in the population in poverty for A-zones and increase of population receiving social security benefits in V-zones, both relative to X-zones.

Table 7. Regression for income.

	Percent Receiving Social Security	Percent Unemployed	Percent Poverty	Spatial Lag (Percent Poverty)
A-zone	0.05	0.024	0.101 **	0.088 **
	(0.044)	(1.3)	(2.11)	(1.97)
V-zone	0.215 ***	−0.027	−0.06	−0.076
	(0.073)	(0.91)	(0.81)	(1.1)
Inundation level 2	−5.247 **	−1.186	−4.808 *	−5.646 **
	(2.635)	(1.1)	(1.73)	(2.17)
Inundation level 3	−7.802 **	−3.223 **	−9.141 **	−9.314 **
	(3.899)	(1.99)	(2.23)	(2.44)
Inundation level 4	−10.784 **	−2.346	−6.735	−6.628
	(4.977)	(1.14)	(1.3)	(1.37)
Inundation level 5	−13.142 **	−3.406	−2.111	−2.355
	(6.547)	(1.27)	(0.31)	(0.37)
Lag dependent variable	−0.589 ***	−0.850 ***	−0.453 ***	−0.468 ***
	(0.089)	(7.55)	(6.8)	(7.52)
R^2	0.24	0.31	0.29	0.27
N	152	152	152	152

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000.

Table 8 reports regression coefficients for age variables. There is not a statistically significant change for populations 65 and older in any of the inundation levels. However, results reveal a statistically significant decrease in the proportion of population 5 years and under in inundation levels 3 and 4, relative to level 1. Moreover, we estimated an increase in the population 65 and older in V-zones, relative to X-zones, which is also supported by the increased population receiving social security income in these zones.

Table 8. Regression for age.

	Percent 65 and Older	**Percent 5 Years or Less**	**Spatial Lag (Percent 5 Years or Less)**
A-zone	0.026	0.016	0.014
	(0.028)	(0.91)	(0.86)
V-zone	0.136 ***	−0.005	0.003
	(0.046)	(0.16)	(0.1)
Inundation level 2	−0.674	−0.184	−0.412
	(1.665)	(0.18)	(0.42)
Inundation level 3	−1.126	−2.572 *	−2.960 **
	(2.488)	(1.66)	(2.02)
Inundation level 4	−2.204	−3.922 **	−4.386 **
	(3.166)	(1.99)	(2.36)
Inundation level 5	−6.077	−2.308	−2.863
	(4.131)	(0.9)	(1.18)
Lag dependent variable	−0.518 ***	−0.842 ***	−0.791 ***
	(0.089)	(7.3)	(7.18)
R^2	0.21	0.31	0.30
N	152	152	152

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000.

In Table 9, the results for various indicators of marginalized populations are reported. We estimated the proportion of the female population decreased in a statistically significant manner for inundation levels 3 and 4, relative to inundation level 1. Results also reveal that the percentage of non-white population decreased in inundation levels 2 and 4, relative to level 1. Similarly, the results for the percentage of female-headed households also decreased in a statistically significant manner for inundation levels 2 and 3. There is no significant change in the percentage of the population with no vehicle for any of the inundation levels examined.

Table 9. Regression for marginalized populations.

	Pct. Female	Pct. Not White	Pct. Less than 12th Grade	Pct. no Vehicle	Spatial Lag (Pct. no Vehicle)	Pct. Female Headed Household	Spatial Error (Pct. Female Headed Household)
A-zone	0.031 (0.026)	0.063 (0.97)	0.042 (1.08)	0.057 (1.62)	0.048 (1.49)	0.037 (0.81)	0.037 (0.83)
V-zone	0.079 * (0.041)	−0.185 * (1.87)	−0.073 (1.19)	−0.064 (1.17)	−0.08 (1.59)	−0.106 (1.55)	−0.105 (1.56)
Inundation level 2	−0.315 (1.499)	−6.336 * (1.67)	−0.907 (0.4)	1.058 (0.53)	1.255 (0.68)	−4.966 * (1.93)	−4.594 * (1.66)
Inundation level 3	−1.866 (2.252)	−11.666 ** (2.07)	−5.27 (1.56)	−2.551 (0.85)	−2.179 (0.79)	−6.969 * (1.8)	−6.443 * (1.65)
Inundation level 4	−6.253 ** (2.851)	−10.179 (1.43)	−3.481 (0.82)	−1.79 (0.47)	−1.016 (0.29)	−7.636 (1.56)	−7.123 (1.5)
Inundation level 5	−7.469 * (3.783)	−7.394 (0.79)	5.715 (1.02)	−1.834 (0.37)	−1.174 (0.25)	−5.196 (0.79)	−4.596 (0.73)
Lag dependent variable	−0.782 *** (0.116)	−0.379 *** (6.88)	−0.495 *** (7.54)	−0.458 *** (7.01)	−0.440 *** (7.28)	−0.836 *** (14.5)	−0.853 *** (14.34)
R^2	0.26	0.28	0.35	0.28	0.26	0.62	0.6
N	152	152	152	152	152	152	152

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000.

7. Discussion and Limitations, Conclusions and Policy Recommendations

7.1. Discussion and Limitations

The objective of this study was to identify spatial and temporal adjustment patterns to disasters across vulnerable segments of population. Figure 4 shows the conceptual flow diagram for our problem. Findings in this paper offer important insights into the adjustments of socially vulnerable populations in Galveston County following Hurricane Ike in 2008. Overall, the results surprisingly reveal a statistically significant decrease in both the indexed components of social vulnerability, and the individual drivers of it in hazard-vulnerable block groups. These results seem to contradict past studies, which indicate that low income populations stay in high damage areas [21,22]. This study did not find that the drivers of social vulnerability and SV indices changed in a similar fashion to those in New Orleans following Hurricane Katrina, or Miami-Dade following Hurricane Andrew [21,22]. While it may be impetuous to expect similar results for very different geographic areas, with differing social makeup and scales of impact, searching for redundancy in disaster adjustments can aid in policy creation.

One possible explanation for an overall decrease in vulnerability may be the combination of the loss of public housing (e.g., Galveston Island lost a large number of public housing units) and the changes in housing tenure due to coastal gentrification from investors. A recent study also suggested a decrease in socially vulnerable populations in Galveston county, possibly due to the changes in public housing [81]. Further research to link these factors to the change in social fabric in Galveston county will be a fruitful extension of the current research.

It is important to note that this study is limited by spatial scale, block groups within a county. The limitation of spatial scale is important to note for two reasons. Firstly, the smaller scale of the block group may not be capturing the overall migratory effect following Hurricane Ike. While multiple studies show that adjustments at a small scale are heterogeneous based on income, studies at larger scales, i.e., county to county migrations reveal that drivers of social vulnerability, specifically; racial minorities, poor, less educated, and female-headed households are disproportionally subject to larger scale displacement [82–86]. Secondly, we make use of the deductive approach in the creation of a social vulnerability indices, which is typically done at the census tract scale where there is often more socioeconomic data available. Specifically, for this paper we were limited to a subset of variables commonly used to measure vulnerability because of the availability at the spatial and temporal scales, i.e., variable consistency between the years 2000 and 2015 at the block group level. Data permitting, exploring vulnerability indicators along the health margin will be an important extension of the present study in the future.

Communities are extremely complex social systems, especially in disaster events, and the quantitative measures for social vulnerability and methodological approaches for assessing adjustments are not without constraint. Further research should be undertaken to understand the many motivators of adjustments, and limitations for composite measures of social vulnerability at various spatial scales.

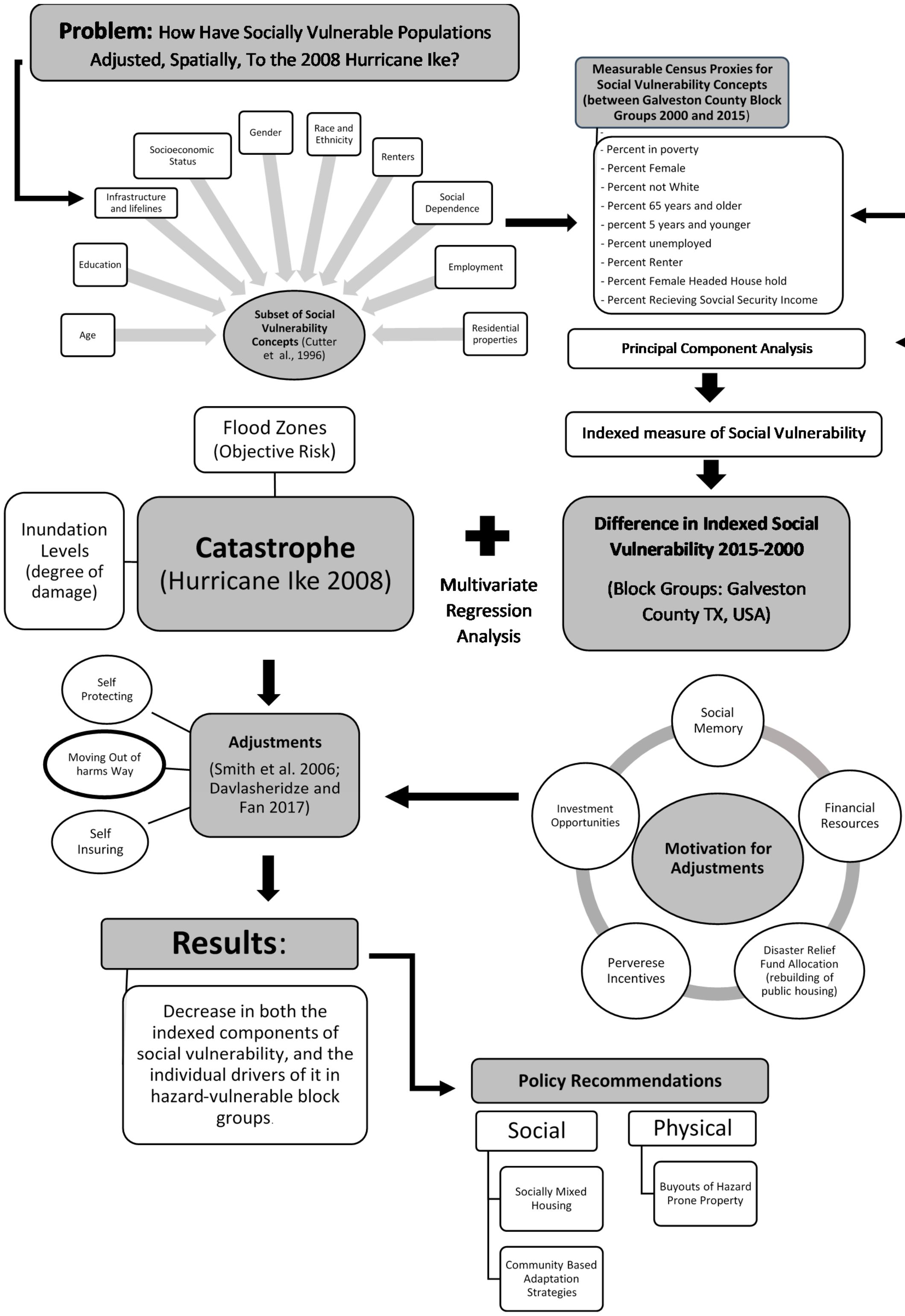

Figure 4. Conceptual flow diagram.

7.2. Conclusions and Policy Recommendations

This study makes significant contributions to the literature by integrating the usage of a social vulnerability index and building upon the various methodological approaches to the hazard of place model developed by Cutter et al. 2003 [20]. Utilizing the social vulnerability model to examine the adjustment of populations provides a link to between the bodies of work. Further, another important contribution is the consideration of spatial effects. Because adjustments post disaster are a spatial phenomenon accommodating for the spatial effects and spatial dependence allows for more robust statistical modeling. Along with accounting for the spatial effects, this study examines spatially driven correlations as a means to analyze post-disaster adjustment. Theoretically, this is an important contribution, as the adjustments of populations are spatially motivated and occur on a geographic scale.

Primary policy recommendations based on this research are taking advantage of location specific sources of resilience, social capital, social integration, and community-based adaptation strategies, such as CBAC's. This may be an imperative strategy to lessen vulnerabilities to disaster for marginalized segments of the population. Specifically, racial integration and revitalization projects which focus on heterogeneity in housing tenure can help to mitigate place-based social exclusion, increase community capital, and decrease vulnerability to disaster events. However, as described in Berke et al. (2019) equitable policies meant to address social vulnerability exclusively may not be enough without focusing specifically on disaster mitigation [87]. In this context, property buyouts in flood prone areas, if properly executed, could enhance community hazard resilience. Evidence suggests it is common for economically disadvantaged populations to reside in more flood prone areas, therefore targeted home buyouts can reduce the perverse incentive to stay in hazard prone areas and mitigate repetitive flood [51,52]. However, it is also important that there is adequate compensation and access to comparable housing nearby. A combination of buying out flood vulnerable housing, and re-building and retrofitting equitable housing in safer locations would be the desirable course of public intervention. In the face of threatened risk due to rising sea levels, a more complex understanding of social motivations for adjustments and vulnerability should be explored and will be an important extension of this study.

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Appendix A

Table A1. Summary Statistics 2000.

	Shares in 2000			
Variable	**Mean**	**Std.Dev**	**Min**	**Max**
Percent in poverty	20.12	14.76	0	78.63
Percent female headed household	15.10	11.08	0	57.21
Percent no vehicle	8.66	10.51	0	71.76
Percent unemployed	5.43	4.47	0	22.40
Percent receiving social security income	30.16	12.80	0	72.88
Percent renter	37.00	24.24	0	94.45
Percent of mobile homes	4.76	9.96	0	62.90
Percent not white	45.39	23.93	0	100.00
Percent 5 years and under	5.85	4.42	0	19.85
Percent 65 years and older	14.49	7.93	0	39.93
Percent female	51.01	6.38	22.23	68.84
Percent with less than a 12th grade education	15.68	11.49	0	51.73

Notes: the sample contains 250,158 observations (Population in 2000). Sources: U.S. Census Bureau; American Community Survey, 2000.

Table A2. Summary Statistics 2015.

Variable	Shares in 2015			
	Mean	Std. Dev	Min	Max
Percent in poverty	26.73	16.39	0	86.77
Percent female headed household	44.11	18.36	0	94.66
Percent no vehicle	10.28	11.65	0	69.73
Percent unemployed	4.78	4.84	0	53.72
Percent receiving social security income	25.45	10.94	0	63.10
Percent renter	35.23	22.51	0	98.22
Percent of mobile homes	5.97	10.88	0	55.67
Percent not white	42.70	26.19	3.62	100.00
Percent 5 years and under	7.92	3.40	0	17.08
Percent 65 years and older	12.55	7.00	0	43.44
Percent female	51.36	4.68	27.30	65.12
Percent with less than a 12th grade education	23.54	14.15	0	100.00

Notes: the sample contains 308,163 observations (Population in 2015). Sources: U.S. Census Bureau; American Community Survey, 2015.

Table A3. Variables and Concepts.

Concept	Variable Measuring Concept
Socioeconomic status (income, political power, prestige)	Percent in poverty
Gender	Percent female
Race and Ethnicity	Percent not white
Age	Percent 65 years and older Percent 5 years and under
Employment loss	Percent unemployed
Renters	Percent renter
Family Structure	Percent female headed household
Social dependence	Percent receiving social security income
Education	Percent with less than a 12th grade education
Infrastructure and Lifelines	Percent no vehicle
Residential Property	Percent of mobile homes

Sources: Cutter et al. (2003).

Table A4. Summary statistics for SV.

Variable	Mean	Std.Dev	Min	Max
2000 SV	0.02	0.95	−1.86	2.76
2015 SV	0.09	0.51	−1.39	1.77

Source: The authors.

Table A5. Spatial Autocorrelation Tests.

	LM Value	Probability
Dpctpoverty		
LM Error	0.169	0.681
LM LAG	3.741	0.053 *
Dpctheadfem		
LM Error	4.933	0.026 **
LM LAG	0.062	0.804
Dpercentnov		
LM Error	0.054	0.817
LM LAG	3.279	0.07 *
Dpctunemplo		
LM Error	0.003	0.956
LM LAG	0.342	0.559
Dpctsocials		
LM Error	0.717	0.397
LM LAG	1.346	0.246
Dpercentren		
LM Error	2.212	0.137
LM LAG	4.088	0.043 **
Dpctmobile		
LM Error	0.002	0.967
LM LAG	0.812	0.367
Dpctnotwhit		
LM Error	1.754	0.185
LM LAG	0.005	0.942
Dpctyoung		
LM Error	2.244	0.134
LM LAG	3.318	0.069 *
Dpctold		
LM Error	0.162	0.687
LM LAG	0.569	0.451
Dpctfemale		
LM ERROR	0.997	0.318
LM LAG	2.312	0.128
Dpctunder12		
LM Error	2.021	0.155
LM LAG	0.05	0.824
DSV		
LM Error	0.059	0.808
LM LAG	0.117	0.732

Notes: * $p < 0.1$; ** $p < 0.05$; LM stands for LaGrange Multiplier Test Statistic. Source: The authors.

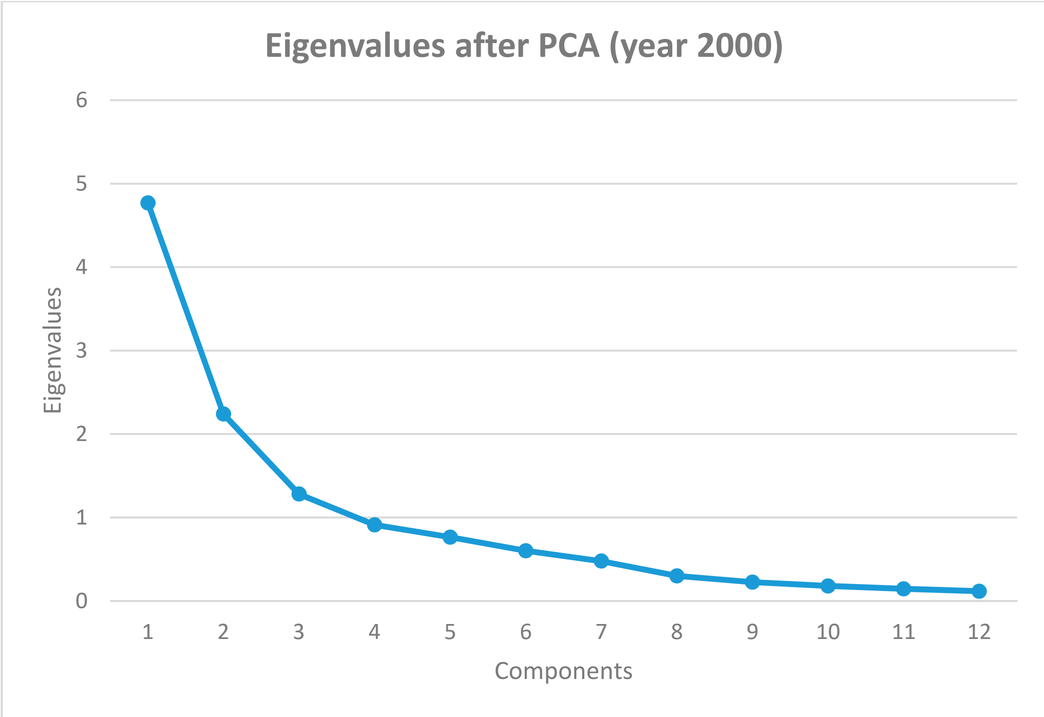

Figure A1. Eigenvalues after PCA (year 2000). Notes: Shows the components and their Eigenvalues for the year 2000.

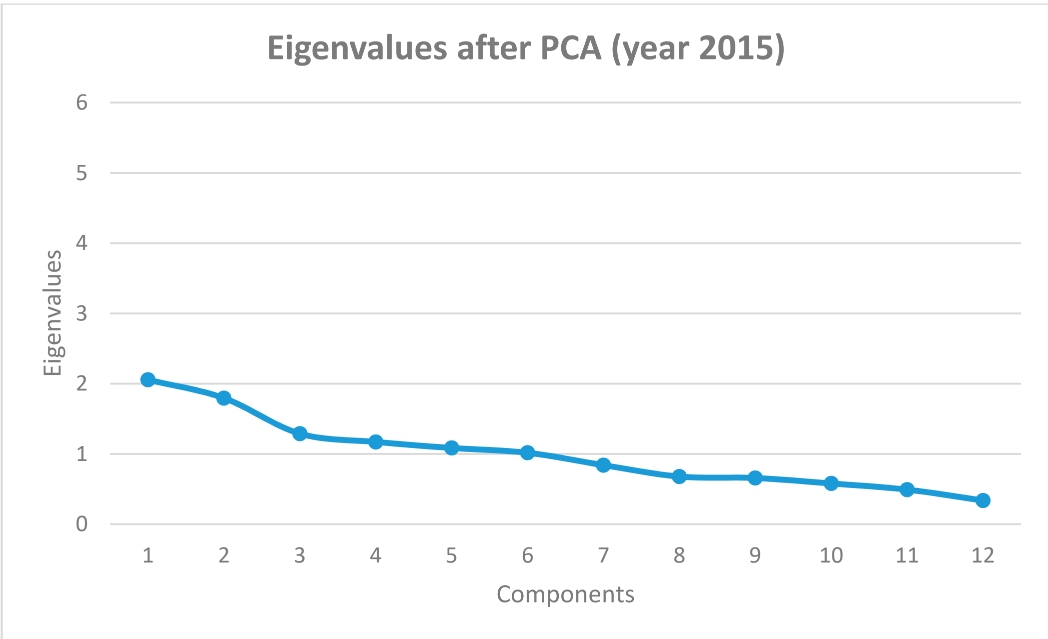

Figure A2. Eigenvalues after PCA (year 2015). Notes: Shows the components wand their Eigenvalues for the year 2015.

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