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Measuring Historic and Longitudinal Social Vulnerability in Disaster-Prone Communities: A Modification to the Centers for Disease Control and Prevention Social Vulnerability Index (CDC-SVI)

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Abstract

Objective: Researchers have developed numerous indices to identify vulnerable sub-populations. The Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI) is the most common and highly serviceable, but it has some temporal limitations considering that some variables used in calculating the CDC-SVI were not available before 1980. Changes in societal composition over time can impact social vulnerability. This study defines an alternate, but similar, index that could serve as a surrogate for the CDC-SVI without the temporal limitations.

Methods: An inventory analysis of the historical census data (1960-2018) was used to develop a Modified SVI that allows for historic analyses. To consider the chronic effect of social vulnerabilities, a longitudinal SVI was introduced to elucidate how a community's multidimensional experiences exacerbate vulnerability to disaster events, such as the COVID-19 pandemic. We use Harris County, Texas, in this case study to examine how the Modified SVI performs against the original CDC-SVI.

Results: This Modified SVI was used to generate historical maps, find temporal patterns, and inform a longitudinal SVI measure. The results showed a good agreement among the developed indices and the CDC-SVI. We also observed satisfactory performance in identifying the areas that are most vulnerable to the COVID-19 pandemic.

Conclusions: The Modified SVI overcomes temporal limitations associated with the CDC-SVI, and the longitudinal SVI captures a community's multidimensional experiences that exacerbate a community's vulnerability to disaster events over time.

Disasters and other extreme events impose a significant burden on existing infrastructure systems. Communities are often tasked with the responsibility of preparing for disaster events and planning for disaster management and recovery to protect its citizens. However, there are a variety of factors that may undermine or impair a community's ability to prevent suffering or loss due to a disaster event. These factors are often related to the community's social vulnerability. Minimizing such vulnerabilities could benefit community members by reducing human suffering and financial loss. Researchers have documented how racial minority communities over the years have experienced multidimensional poverty and lack of resources, including poor access to healthcare, transportation, healthy foods, and other basic needs.[1] Unfortunately, both historic and current policies create inequitable situations for these populations.[2]

To identify these vulnerabilities, government agencies have developed numerous indices with different applications, such as the Social Deprivation Index[3] and the Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI).[4] Created by the Geospatial Research, Analysis, and Services Program (GRASP). The CDC-SVI applies statistical methods to determine social vulnerability of each census tract based on 15 variables, which all fall under 1 of the 4 following themes: (1) socioeconomic status (SES), (2) housing composition and disability, (3) minority status and language, and (4) housing and transportation.[4] It has been established that each of the 4 themes of SVI (SES, household composition and disability, minority status and language, housing type and transportation) is related to health outcomes. For example, earlier work has shown that SES is significantly associated with physical health[5] and in particular, lower SES is linked to poorer health outcomes as well as increased mortality and morbidity.[6–8] More recent studies have noted that SVI is associated with an increased risk of coronavirus disease 2019 (COVID-19) fatality.[9,10] Persons with disabilities report higher rates of chronic diseases than the general population.[11] Racial and ethnic minority groups in the United States experience higher rates of illness and death across a broad range of chronic diseases,[12] and the language barrier for non-English speaking patients may lead to poor health outcomes, poor compliance, and poor understanding of health conditions.[13] Substandard housing conditions and, particularly, crowded housing, has also been linked to worse health outcomes[14] and higher rates of infectious disease.[14,15] Additionally, transportation barriers impact health-care access and thus health outcomes.[16]

The generated SVIs are meant to guide public health officials and local leaders to better prepare for and respond to disaster events; they serve as a summary of community level social determinants and as a measure of disaster resilience. Accordingly, the SVI database is frequently used to study hazard mitigation and management. For example, earlier work[17] evaluated social vulnerability indicators in relief preparation for fires. Another study used SVI data to investigate hazard mitigation planning.[18] Hahn and colleagues examined the compounding effects of social vulnerability on mental and physical health. They reported that communities that experienced a natural disaster in the previous five years had a higher incidence of poor mental health than those that had been disaster free.[19] More recently, Rickless and colleagues explored demographic indicators of vulnerability and access to medical care following Hurricane Harvey.[20]

Despite the widespread use of the SVI, it has a fundamental limitation that should be considered. The choice of the 15 variables categorized into the 4 themes temporally limits the use of SVI to recent years, limiting its applicability for historical and/or longitudinal analyses. Known limitations of SVI include the use of census data to calculate the index. This limitation arises because some of the variables used in calculating SVI were not available before 1980. For example, information on persons who speak English "less than well," "Per Capita Income," and housing type information, among others, were not collected in historical census data. The cross-sectional nature of census data impedes the ability to capture important information on vulnerable communities, such as composition and environment, that may change quickly in intercensal years.[21,22] Additionally, using census data does not take into consideration other social risk factors, such as occupation,[21,23] physical geography features, such as fire-prone areas,[22] or any community-specific variables. Because of this, interpretation of the SVI is restricted to the variables included in its calculation.

With constant transformations in societal composition comes the subsequent change in social vulnerability. These changes in vulnerability emphasize characteristics that make individuals and communities more or less susceptible to disaster events and can also influence their ability to respond. Earlier work shows a trending reduction in social vulnerability nationwide, with regional variability, suggesting that a one-size-fits-all approach would be ineffective in improving resilience.[24] Instead, Cutter and Finch[24] propose "place-specific variability within the broader federal policy guidelines." To overcome these obstacles, many have suggested incorporating local community-specific information and even taking into account other vulnerable facilities like hospitals and schools.[21] Authors like Paulino et al.[22] adjusted their model in 2021 to account for features that are unique to the lived experiences and environment of those in such vulnerable communities. Implementing robust evidence-based models also has been shown to potentially overcome the restrictions brought on by indicator-based approaches.[25] In fact, recent research highlights the value of developing machine learning algorithms to improve the accuracy of predicting vulnerability of areas, as some indicators and features may be more important than others.[26]

Considering these limitations, it is essential to create an alternate, but similar, index that could serve as a surrogate for the CDC-SVI without the aforementioned temporal limitations. This study fills the gap by introducing such a surrogate. To do this, we conducted an inventory analysis of the historical census data (1960-2018) and developed a modified SVI that allows for historic analyses and can generate historical maps, find temporal patterns, and inform a longitudinal SVI measure. Because social vulnerabilities are cumulative, a longitudinal SVI should paint a clearer picture of how a community's multidimensional experiences exacerbate social vulnerability to disaster events. We use Harris County, Texas, as a case example, to examine how the modified SVI performs against the original CDC-SVI.

Methods

Study Area

In addressing social vulnerability, total population and diversity play important roles. Harris County, (Figure 1) located in southeastern part of Texas, is the third most populous county in the United States and the most populous one in Texas.[27] Additionally, this county has the third most diverse population in Texas and is among the top 20 counties in the United States (ranked 15th, https://www.niche.com/places-to-live/search/most-diverse-counties/) with more than 60% of its residents identifying as Hispanic or Black. Despite this, African American and Hispanic Texans are more than twice as likely to live below the poverty line as their White and Asian counterparts (The Center for Public Policy Priorities 2019). These minority-majority populations live within 15 miles of other higher socioeconomic status (SES) communities who enjoy 21 additional years of average life expectancy, and $50,000 more in average income.[28] Furthermore, this county has a historical record of natural disasters, especially hurricanes and severe storms. Among them are Tropical Storm Allison (2001), Hurricane Ike (2008), Memorial Day Flood (2015), Tax Day Flood (2016), and Hurricane Harvey (2017).[29] More recently, a total of 523,163 positive cases of COVID-19, with a mortality (5409 deaths) to morbidity rate of 1.03% (as of September 12, 2021), were reported in the county due the COVID-19 pandemic.

Within the study area, we were especially interested in examining changes in the social vulnerability of 4 neighborhoods: Acres Home, Kashmere Gardens, Third Ward, and Sunnyside. These 4 communities in the greater Houston area have a high percentage of non-Hispanic African American residents: Kashmere Gardens (59.46%), Sunnyside (79.97%), Third Ward (64.57%), and Acres Home (55.11%). We selected these 4 communities because they are included in the top 10 Super Neighborhoods[30] with the highest proportion of African Americans. They are historically well-established African American communities in which the research team has worked in the past.

Data Acquisition and Preparation

To investigate the temporal changes in social vulnerability, the analysis was performed on data compiled for the period of 1960-2018. The original census data were used for 1960-2010 and, for 2018, the American Community Survey (ACS) was used. The National Historical Geographic Information System (NHGIS) database[31] was used to download the census data (1960-2018) at the census tract level for the entire United States, as well as the shapefile files for the corresponding census tract boundaries.

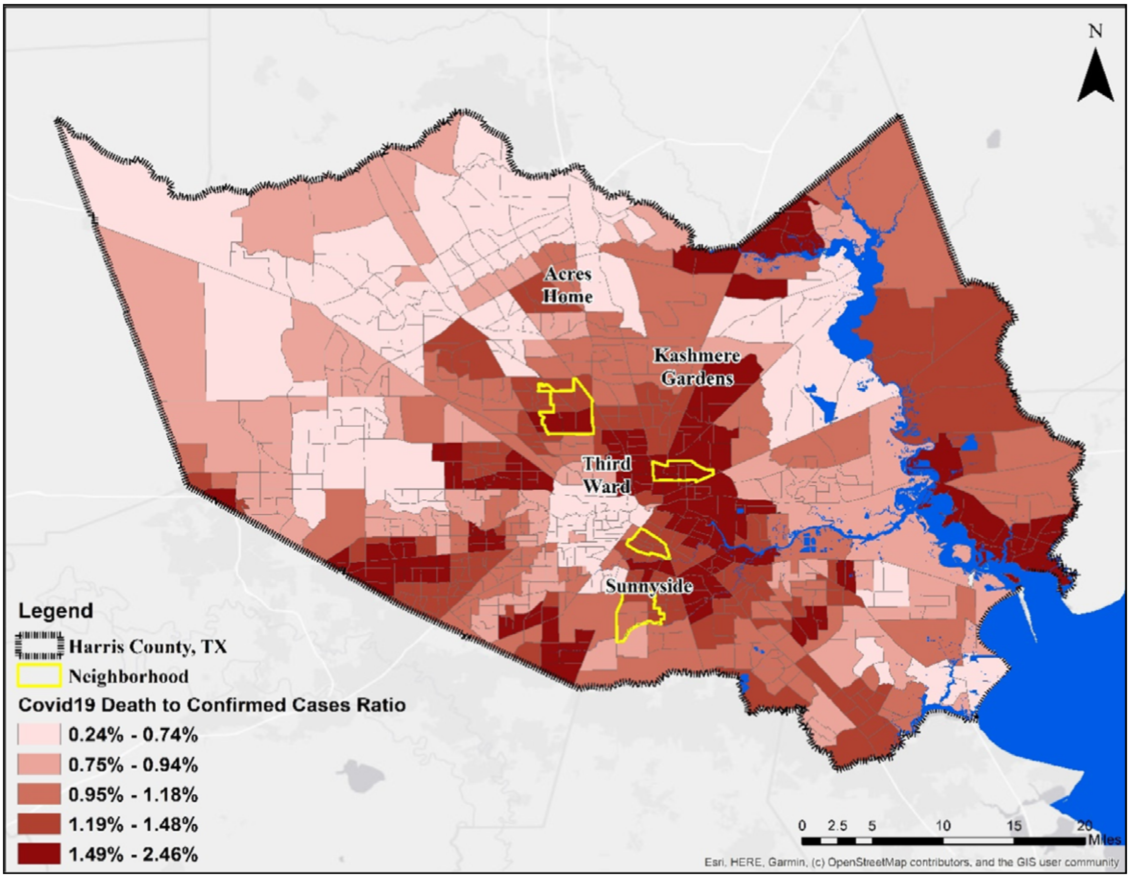

Figure 1. The ratio between the deaths and confirmed cases of COVID-19 in Harris County, Texas, as of September 12, 2021. The location of 4 historically underrepresented neighborhoods within the study area is also shown.

Harris County's COVID-19 data at the zip code level were compiled from the Harris County/City of Houston COVID-19 Data Hub (https://covid-harriscounty.hub.arcgis.com/pages/cumulative-data), which is maintained by the Harris County Public Health and Houston Health Department. The underrepresented neighborhood boundaries (shapefile) were clipped, in ArcMap Desktop 10.8.1, from the Super Neighborhoods shapefile acquired from the City of Houston Geographic Information System (COHGIS) database (https://cohgis-mycity.opendata.arcgis.com/datasets/MyCity::super-neighborhoods/about). For Harris County, the total number of confirmed COVID-19 cases and deaths at the zip code level were compiled from the Harris County Public Health (HCPH) database.[32]

Normalized to the population, the number of confirmed cases and deaths of COVID-19 is not a good indicator of vulnerabilities at the zip code level. This is due to the complex nature of disease spread (e.g., a gathering might spike the number of cases) and the potential error in normalization. The error could occur when only a small portion of large population has been exposed to the disease, but a large percentage of people with the disease pass away. To address this issue, a ratio was defined by dividing the total number of deaths due to COVID-19 and total number of confirmed cases. Finally, to have consistent spatial resolution in this study, the zip code-level COVID-19 data were converted to tract-level using the "Intersect" tool in ArcMap and "Pivot Table" in Microsoft Excel. The area was used to calculate partial weights, as each tract intersects with one or more zip codes. The weighted average of zip codes' COVID-19 data was used to estimate the ratio of deaths to the confirmed cases at the census tracts levels (Figure 1).

Variable Selection for Modified SVI

We conducted an inventory analysis, on the list of existing census variables for the selected time periods, to find the variables most similar to the ones used in the CDC-SVI. The goal was to select the variables that had been consistently recorded during the study timeline. In theme 1 of the CDC SVI (SES), we used all variables except per capita income, due to the absence of consistent historical data. This should not be problematic as the "persons below poverty line" variable, which is included in this theme, could represent the effect of income as well. For "Household Composition & Disability" (theme 2), the dataset in 1960 did not include disability data. Furthermore, persons aged "19 and younger" was used instead of "17 and younger" due to the different age classifications in the 1960 census. Minority and language barriers were replaced by African American and White to Non-White Ratio due to the lack of historical racial, ethnic, and language datasets for theme 3 (Minority Status & Languages). Additionally, no historical data were found on "housing in structures with 10 or more units estimate" and "persons in institutionalized group quarters" for the "Housing Type & Transportation" theme. Finally, and for the same theme, bad quality housing was used instead of mobile homes for 1960. The list of final variables (exacts or approximates) for each of the 4 themes, used in the CDC SVI, is provided in Table 1. After

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Table 1. List of exact or approximate variables used for the temporal analysis, grouped by the themes used in the CDC SVI

Theme	CDC SVI	1960	1970-2018
1	Persons below poverty estimate	✓*	✓
	Civilian (age 16+) unemployed	✓	✓
	Per capita income	×	×
	Persons (age 25+) with no high school diploma	✓	✓
2	Persons aged 65 and older	✓	✓
	Persons aged 17 and younger	Persons aged 19 and younger	✓
	Civilian noninstitutionalized population with a disability	×	✓
	Single parent household with children under 18	✓	✓
3	Minority (all persons except white, non-Hispanic)	African American	African American
	Persons (age 5+) who speak English “less than well”	White to Non-White Ratio	White to Non-White Ratio
4	Housing in structures with 10 or more units estimate	×	×
	Mobile homes estimate	Bad Housing Quality	✓
	At household level (occupied housing units), more people than rooms estimate	✓	✓
	Households with no vehicle available	✓	✓
	Persons in institutionalized group quarters	×	×

downloading the raw data and the associated text files (i.e., variable names), for each , year, the data were spatially filtered using Texas as the state and Harris County as the county. The filtered data were exported to a new Excel sheet where some basic calculations were conducted to determine each of the variables listed in Table 1.

Calculating Modified SVI

Due to the use of different variables compared with the original CDC SVI, we refer to the temporal index used in this study as Modified SVI. A similar approach to the CDC SVI methodology was used to calculate the Modified SVI. For each variable, we calculated the percentile ranking of each tract at each year of interest with regards to the other tracts in Harris County in Microsoft Excel. To do this, for each variable at each year, the tracts were ranked, and their rank was divided by the total number of tracks in Harris County at that specific year plus 1 as follows:

$$Percentile\ Ranking_{v,t,i} = \frac{Tract\ Ranking_{v,t,i}}{Total\ Number\ of\ Tracts_t}$$

Where v, t, and I represent the variable of interest, time (year), and tract of interest, respectively. Next, the percentile rankings for all variables within a theme were summed up and ordered to determine theme-specific percentile rankings. Finally, the sum of the sums for each theme was calculated and ordered to determine the overall percentile rankings for each year.

The overall percentile rankings for all years were exported to ArcMap Desktop 10.8.1 to generate historical maps. For all years, tracts with less than 1000 population were shown with a distinguished symbology. Two different approaches were applied to compare the Modified SVI and the CDC original SVI: (1) visual inspection using the 2018 census data in Harris County, and (2) correlation analysis among the SVIs (2018) and the ratio between the deaths and confirmed cases of COVID-19 as of September 2021.

Longitudinal SVI

To calculate Longitudinal SVI and capture the long-term vulnerabilities, an inverse distance weighted (IDW) interpolation method (with the power parameter equal to 1) was applied to the historical SVIs by using the time difference between each historical SVI and 2021 (year of COVID-19 data) as the distances. The following formula was used:

$$Longitudinal\ SVI_{2021} = \frac{\sum_{t=1960}^{2018} W_t \times SVI_t}{\sum_{t=1960}^{2018} W_t}$$

$$W_t = \frac{1}{(2021 - t)}$$

In which t is the time when the historical SVI is available, W_t is the weight of associate historical SVI (SVI_t) at the time t. A spatial analysis is required to estimate the historical SVIs (SVI_t) at the borders of 2018 census tracts due to the changes in the border of tracts over years. A similar method, applied in converting COVID-19 data at the zip code levels to the census tract levels, was used here as well. An intersect in ArcMap Desktop 10.8.1, followed by a Pivot Table analysis in Microsoft Excel, was performed for each of the historical Modified SVIs and the 2018 SVI.

Results

All census data required to replicate the results, the CDC SVI, Modified SVI (all years), and Longitudinal SVI, are available as a supplementary file.

Modified vs CDC-SVI

Modified and CDC-SVI in Harris County using the 2018 census data are shown in Figure 2. A general agreement between the 2 indices could be observed in the entire country. Such agreement was confirmed by the correlation analysis that showed a significant and strong correlation (P-value <0.05 and r = 0.87). This strong correlation suggests that the modified SVI is synonymous with the original SVI and could be used as a surrogate for similar applications of the CDC-SVI. The correlations among the Modified and CDC SVIs and the ratio of deaths and confirmed cases of COVID-19 were significant (P-value < 0.05) with correlation coefficients of 0.48 and 0.56, respectively.

Despite the general agreement between the two indices, we observed some differences. For example, among the 4 neighborhoods of interest in this study, 2 (Kashmere Garden and Acres Home, see Figure 2) showed different level of vulnerabilities. These differences are driven partly by changing per capita income, definition of minorities, and language barriers. The largest difference was observed in the Kashmere Garden where the African

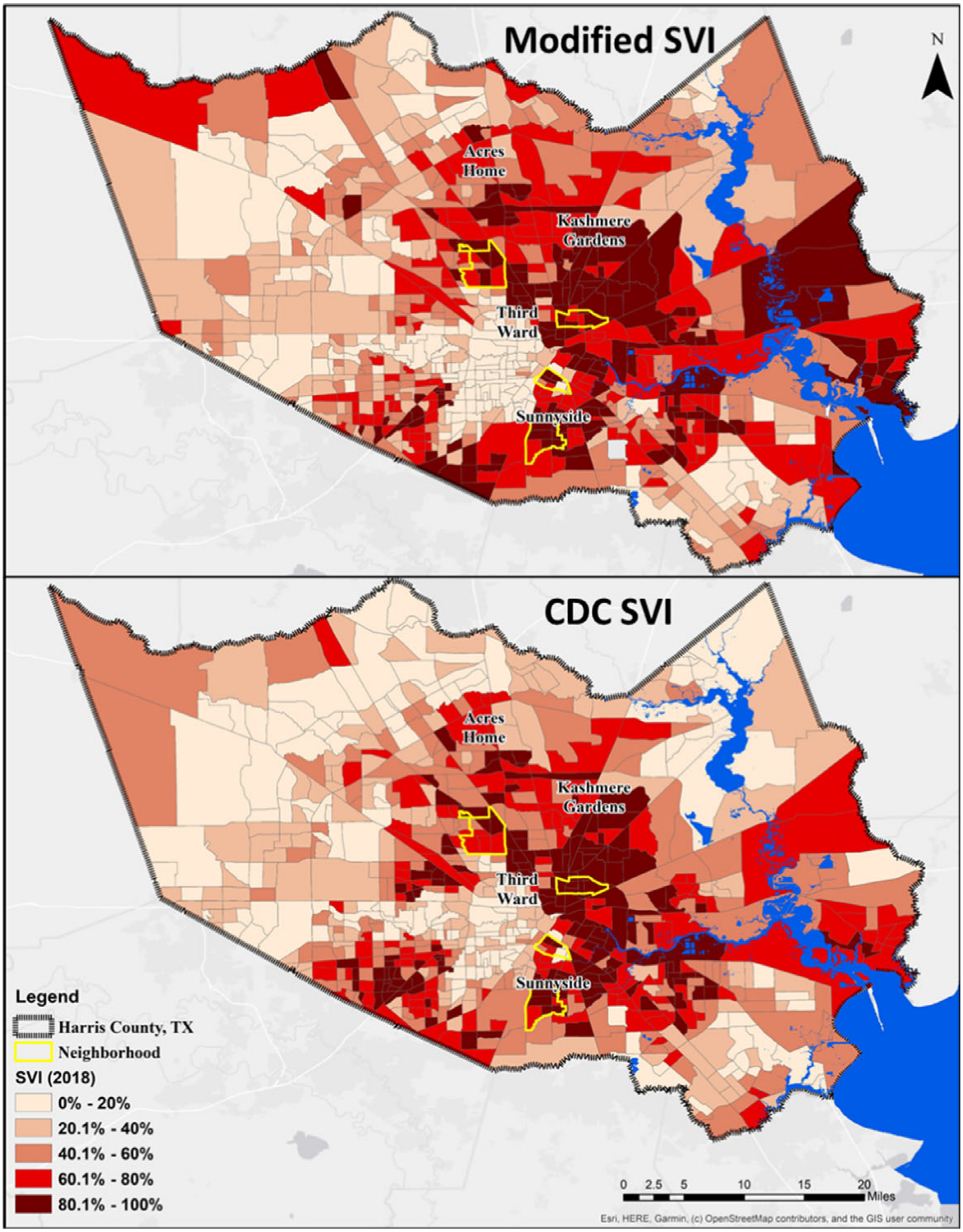

Figure 2. Modified SVI (top) and CDC SVI (bottom) in Harris County Texas for 2018.

American ratio is relatively smaller than the other neighborhoods (see Table 2), while the Hispanic population is higher.

Historical Modified SVIs

The new Modified SVI developed in this study provides an opportunity for adding a temporal dimension to the classic spatial analysis inherent in the CDC SVI. Modified SVIs in Harris County, Texas, from 1960 to 2010 are shown in Figure 3. These maps highlight major changes in socioeconomics, population density, and social vulnerabilities over time.

The abundance of hatched areas in Figure 3, 1970 compared with 1960, shows the migration of populations to the suburbs. Areas closer to the eastern part of Harris County, where NASA's Manned Spacecraft Center (1962, https://www.houston.org/timeline) and petrochemical plants were built, were occupied by more vulnerable populations. It is worth noting that the maps shown in Figure 3 are based on decadal census data, which reflect

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Table 2. Summary statistics for race and median income in the 4 neighborhoods of interest

Variable	Kashmere Gardens	Sunnyside	Third Ward	Acres Home
African American[1]	51%	71%	60%	53%
Hispanic[1]	45%	21%	13%	38%
Income[2]	$27,626	$27,102	$34,058	$41,358

[1]Data from https://discovery.houstoncc.org/kashmere-gardens/
[2]Data from https://www.houstonstateofhealth.com/indicators/index/

the changes in data in 10-year periods ending at the census year. The methodology developed in this study could be applied to make the temporal resolution finer to investigate more gradual changes (if data are available). Between 1970 and 1980, approximately 200 major firms, such as Shell Oil Co (1971, https://www.houston.org/timeline), moved their headquarters, subsidiaries, and divisions to Houston. A major change in the modified SVI distribution could be observed between 1980 and 1990. While the economy was great-booming in the early 1980s (employment peaks at 1,583,400 in March 1982), a recession caused more than 220,000 job losses in 1987. Such a change in the economy led to redistribution in the population. Meanwhile, there were changes in the numbers and boundaries of the census tracks within Harris County during 1980-1990. Using a finer spatial (census groups) and temporal resolution (5 year) could help interested researchers to have a better understanding of this shift. With the passage of time and continuous economic growth in the Houston area (economic recovery in 1990), to date, there has been no sign of improvement in the areas with most vulnerable population.

Longitudinal SVI

The Longitudinal SVI is shown in Figure 4. The main difference between the Longitudinal SVI (Figure 4) and 2018 Modified SVI (Figure 2) could be observed in the southern, eastern, northwestern, and southwestern parts of Harris County. In these areas, the Longitudinal SVI showed less vulnerability compared with the situation in 2018. This could suggest the expansion of areas with vulnerable populations. The Longitudinal SVI showed the most vulnerability in the 4 neighborhoods of interest, which indicates some improvement in life quality in the recent years. Using Longitudinal SVI, instead of the 2018 Modified SVI in the correlation analysis with the ratio of deaths and confirmed cases of COVID-19, caused an improvement in the correlation coefficient (from 0.48 to 0.50). Such an improvement indicates the importance of considering chronical vulnerabilities in estimating the response of population to disasters.

Discussion

This study sought to develop a Modified SVI to overcome the temporal limitations associated with the CDC-SVI, and to introduce the use of historic and longitudinal SVI to examine how a community's multidimensional experiences exacerbate social vulnerability to disaster events over time. Although several limitations of the CDC-SVI have been documented in the literature, few studies have actually developed alternative measures. To the best of our knowledge, this is one of the few studies to develop a Modified SVI approach to the CDC-SVI. Methodological studies of this nature are useful to other researchers examining social vulnerability as they are able to use similar methodology to replicate and capture community characteristics for historical analysis, and to examine how vulnerabilities in specific geographies have changed over decades. For cross-sectional and prospective studies on vulnerabilities, the longitudinal SVI presents an alternative because it reveals a temporal and time effect on how a community's multidimensional experiences exacerbate vulnerability to disaster events. Using historical and/or longitudinal SVI may minimize the limitations of CDC-SVI.

In our use case, we compared vulnerabilities in 4 African American communities with the rest of Harris County. Findings from our use case suggest general agreement between the original and Modified SVI in recent time periods, evidenced by significant positive correlations. These significant correlations provide additional validation to our Modified SVI use for historic and longitudinal analysis. Environmental justice and hazard vulnerability research reveals that racial/ethnic communities are disproportionately vulnerable, with exacerbations in economic and social inequalities. Research on various disasters, including, hurricanes, floods, and, most recently, the COVID-19 pandemic, underscore how racial/ethnic minorities often face the most challenges in receiving government aid to recover after the natural disaster hits.[33] For example, of those who applied for disaster assistance from FEMA following Hurricane Harvey, African American residents appeared to face the most challenges in receiving government aid to recover after the devastating storm.[33,34] African American individuals, in general, experience a higher burden of chronic disease and multidimensional economic, environmental, and social hurdles compared with their White counterparts.[35] These vulnerabilities, fueled by multidimensional economic and environmental disparities mean that African American communities are in a vulnerable state and ill equipped for severe climate change or a pandemic.

In the face of disasters, the longitudinal SVI can be used to identify which communities are most vulnerable, and, therefore, will likely need extended support in disaster recovery. Such information could be used to estimate the amount of supplies a community may need (such as food, water, and medicine), and also identify geographic areas needing emergency shelters, based on chronical precedence on social vulnerability. The historical Modified SVIs (with various temporal and spatial resolution) could be used to understand the temporal changes in the vulnerability of communities and correlate them to proper causes. Such cause-effect studies could not be conducted without proper snapshots of spatial vulnerability over time, such as the one suggested here.

While these modified indices offer beneficial insight for emergency or disaster preparedness and recovery, they are not without their own limitations. Individually, they are only a single portion of the larger equation surrounding social vulnerability, and, alone, cannot adequately encompass the complex nature of vulnerability. Rather, the indices may be considered just a first step in screening vulnerable populations and to overcoming the temporal limitations of the CDC-SVI.

With the frequency of climate change events and global health crises, the need for information on historic and longitudinal social vulnerabilities is more important than ever. It presents a holistic view of the community's experiences, which, in turn, helps us better prepare for and recover from future disasters. Future research should adopt the Modified SVI for other geographic areas to ensure fidelity.

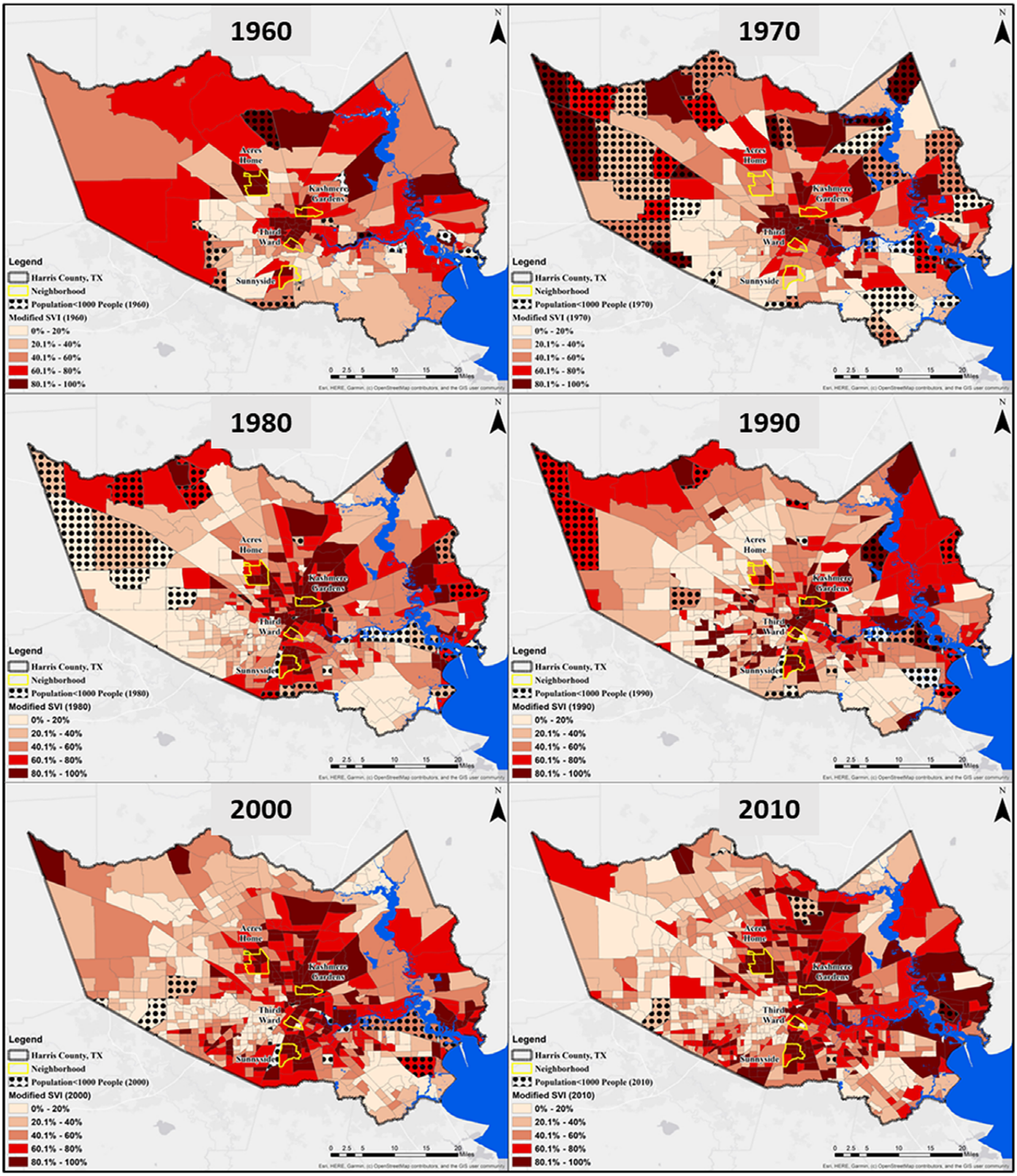

Figure 3. Modified SVI in Harris County, Texas, from 1960 to 2010. The hatched areas depict the census tracts with a population of less than 1000.

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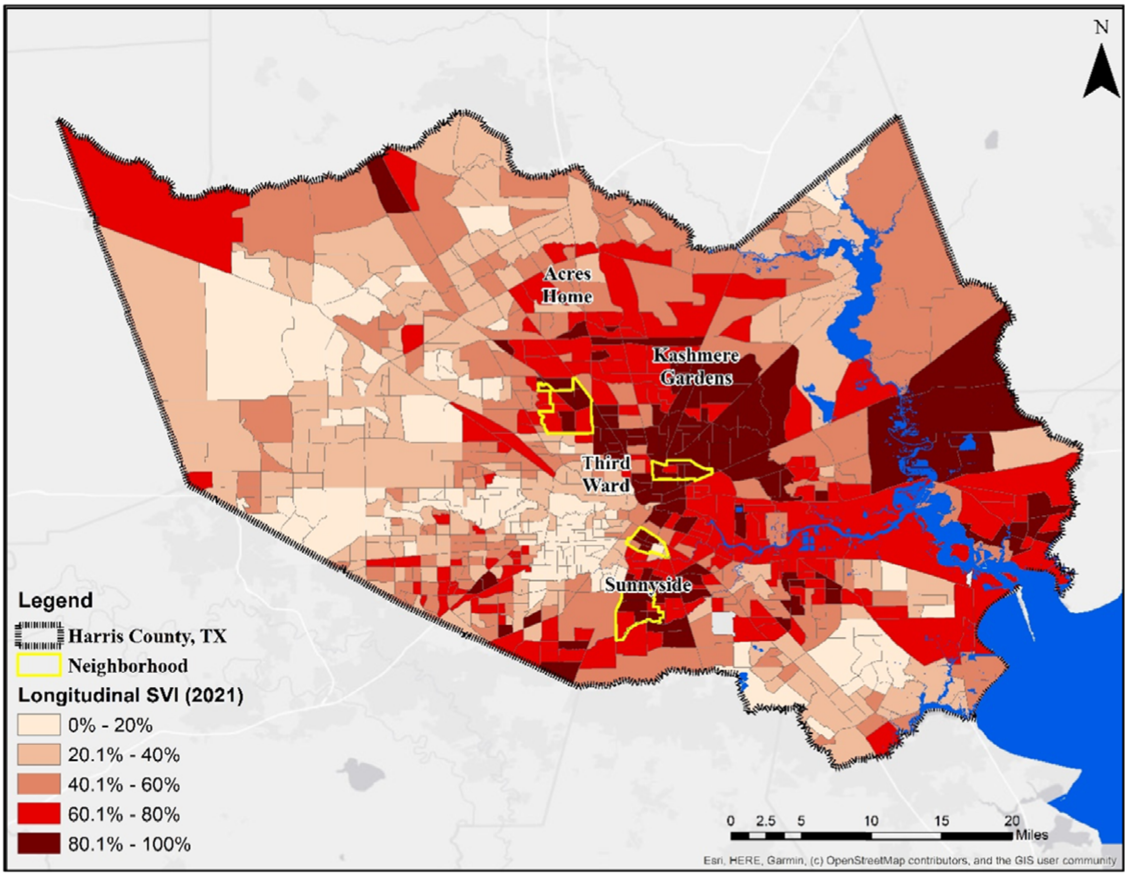

Figure 4. Longitudinal SVI in Harris County Texas for 2021.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/dmp.2023.29

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