Comparing Social Vulnerability and Population Loss in Puerto Rico after Hurricane Maria

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Abstract

Communities in Puerto Rico saw their populations shrink after Hurricane Maria in 2017. Of the archipelago's 884 census tracts, 613 tracts (69.3%) experienced a net population loss with an average loss of 161 people. To understand the relationship between social vulnerability and post-disaster population loss, informed by theories of environmental migration, I compare a measure of social vulnerability in Puerto Rico to population change in each tract. This study also provides an opportunity to evaluate the validity of the Social Vulnerability Index (SVI) measure in Puerto Rico. Through six regression models, I find that the current 15-variable SVI significantly predicts greater population losses for more vulnerable areas in Puerto Rico, in which the most vulnerable tracts lost 70 more people when compared to tracts at the median. However, using factor analysis to create a revised 10-variable SVI produces an even larger effect size when predicting population loss, in which the most vulnerable tracts lost about 151 more people than the least vulnerable. These results suggest that a 10-variable SVI may have higher construct validity for the context of Puerto Rico and could serve as a foundation for a measure of vulnerability that better reflects local conditions and experiences with disaster. This is the first study to test the relationship between a social vulnerability index and post-disaster population change in Puerto Rico. These findings highlight the need for further investigation of the link between social vulnerability and post-disaster migration and underscore the importance of context-specific measures of social vulnerability.

Keywords: environmental migration, disaster, vulnerability, Hurricane Maria, Puerto Rico

Introduction

When Hurricane Maria devastated Puerto Rico in 2017, it amplified a yearslong trend of net out-migration which—combined with a death toll as high as 4,645—led to an overall population loss of four percent, or about 129,000 people (Acosta et al., 2020; Kishore et al., 2018). However, population change was not evenly distributed across Puerto Rico, and 69.3% of census tracts experienced a net population loss (Flores & Krogstad, 2019; Santos-Burgoa et al., 2018). Because significant population loss can change the composition of disaster-affected communities, it is important to understand who leaves and who stays, and why. As such, this article investigates the links between post-disaster population change, environmental migration, and social vulnerability. It also seeks to evaluate and refine the Social Vulnerability Index (SVI) for Puerto Rico.

The concept of social vulnerability to disasters has gained traction over the last forty years as a way of explaining the interaction between social inequality and the differential outcomes associated with disasters for people and places (Thomas et al., 2013; Wisner et al., 2004). Social vulnerability describes the uneven distribution of susceptibility to harm or loss from a hazard. This differential in risk aligns with pre-existing inequalities or stratification, demonstrating that vulnerability to disasters is socially constructed (Adger, 2006; Morrow, 1999). Social vulnerability is also increasingly understood as a form of environmental injustice, calling attention to shared root causes (Jerolleman, 2019; Ryder, 2017). Various attempts have been made across disciplines to measure social vulnerability (Adger, 2006; Alwang, 2001; Cutter et al., 2003; Hinkel, 2011; Toro et al., 2012), but others have critiqued and questioned the utility of such measures because of their tendency to incorrectly portray vulnerability as a fixed trait of subaltern groups (Jacobs, 2021; Marino & Faas, 2020). These debates are important, yet outside of academic discussion social vulnerability is increasingly part of the lexicon of practitioners who aspire to reduce inequality and injustice related to disasters. By identifying vulnerable populations ahead of a disaster, they hope to reduce vulnerability and minimize corresponding losses. Therefore, the increasing use of social vulnerability measures and analyses to structure environmental policies and practice warrants ongoing attention from social scientists.

The two measures most commonly used in practice are the Social Vulnerability Index known as SoVI® (Cutter et al., 2003) as well as the SVI created by the U.S. Centers for Disease Control and Prevention (CDC) (Flanagan et al., 2011). In Harris County, Texas, the SVI was recently proposed by county commissioners for use in allocating flood mitigation services to areas with more socially vulnerable populations (Azhar, 2021). The growing popularity of these indices among policymakers and practitioners may be attributed to several key characteristics. They are relatively simple to interpret; use public census data; and can be visualized on a map. However, the increased uptake of these measures in policy and practice has been accompanied by calls for caution from researchers who have tested the internal and external validity of index-based measures of vulnerability (Bakkensen et al., 2017; Rufat et al., 2019; Spielman et al., 2020; Tate, 2012). Some indices have been found to perform inconsistently or produce results counter to theory (Spielman et al., 2020). I share this concern about confirming whether indices measure what they claim to before using them to reduce vulnerability or pursue equity goals in disaster contexts.

Hurricane Maria's devastating impact on Puerto Rico in 2017 serves as a unique opportunity to evaluate the components typically used to measure social vulnerability against disaster outcomes for a context beyond the continental United States. Puerto Rico is the only U.S. territory for which the federal government currently publishes social vulnerability data.

Puerto Rico may have the same census data as the 50 U.S. states, but the data represent a distinct context shaped by a long-standing colonial relationship with the United States. I specifically test the SVI because it is the only open data available on social vulnerability for Puerto Rico for the year before Hurricane Maria, which is necessary for comparing pre-storm social vulnerability to post-disaster population loss. Following approaches used in previous SVI validation research (Rufat et al., 2019), disaster impacts in Puerto Rico are represented by population change at the census tract level from 2016 to 2018 based on 5-year American Community Survey data. This article makes two contributions: 1) an assessment of the validity of the SVI for Puerto Rico, and 2) an evaluation of the SVI's effectiveness in predicting post-disaster population change.

Although researchers have previously discussed the contributions of social vulnerability to environmental migration and climate adaptation (McLeman & Hunter, 2010; Oliver-Smith, 2009; Simon & Riosmena, 2022), this study is the first to test the relationship between a social vulnerability index and post-disaster population change in Puerto Rico. Being able to anticipate trends in migration after disasters would be useful for planners and policymakers, as this information can aid in understanding the needs of those who remain in place during and after disaster. Additionally, this article seeks to strengthen the theoretical link between social vulnerability and environmental migration.

Literature Review

Conceptualizing Social Vulnerability

Social vulnerability has long been recognized as a critical component for understanding disaster risk in both research (Birkmann et al., 2006; Lee, 2014; Morrow, 1999) and practice (Kozel et al., 2008). A recent definition describes vulnerability as "the sociodemographic characteristics of a population and the physical, social, economic, and environmental factors that increase their susceptibility to adverse disaster outcomes and capacity to anticipate, cope with, resist, and recover from disaster events" (Adams et al., 2022). The conceptualization of vulnerability to disasters has evolved over time since it was introduced into disaster literature in the 1960s. Misztal (2011) refers to an "old" and "new" approach to vulnerability, the former characterized by a focus on *physical* vulnerability that originated mainly with natural hazards, such as earthquakes, floods, tornadoes, and wildfires. The latter approach, emerging in the 1980s, focuses on the *social* vulnerability of people or places that is produced by the combination of hazards and social inequality (Misztal, 2011; Thomas et al., 2013). Extending Misztal's framework, I argue there is a third, critical approach to vulnerability research that challenges the "dominant paradigm" (Thomas et al., 2013, p. 5) and discourages the labeling of people, groups, or places as vulnerable because vulnerability is dynamic and situational (Jacobs, 2021; Marino & Faas, 2020; Ryder, 2017). This approach to social vulnerability seeks to explain its root causes while shifting the focus away from those who bear vulnerability and towards the uneven social relations that create risk for some and not for others (Marino & Faas, 2020; Peek, 2019). Whereas the first and second approaches to vulnerability seek technological solutions to reduce the impacts of disasters on vulnerable people, the third approach understands social vulnerability as a form of environmental injustice, a structural-level issue produced by racial capitalism and colonialism that may not be quickly remedied by technological solutions (Jacobs, 2021; Ryder, 2017).

Thus, social vulnerability is best understood and is most useful as a proxy for key sociological concerns (Peek, 2019). People and groups are not inherently vulnerable. Rather, conceptualizations of social vulnerability have commonly demonstrated how people in particular social categories and conditions come to bear differential vulnerability to hazards and disasters as a function of power relations in society (Fothergill & Peek, 2004; Peek, 2019). In Puerto Rico, some of the upstream factors that produce differential vulnerability include its political status as a territory in which U.S. citizens lack voting representation in Congress as well as the organization of Puerto Rico's financial sector, which has been controlled by the federally appointed Fiscal Oversight and Management Board since 2016. These structural conditions have served to deepen the vulnerability of marginalized populations across multiple disasters in Puerto Rico (D. Z. Rivera, 2020). Categories that may influence how people experience vulnerability include age, race, ethnicity, social class, gender, disability, and education, among others (Thomas et al., 2013). Based on one's social position across such intersectional categories, some people may experience relative disadvantage across all stages of disaster (Fothergill & Peek, 2004). At the same time, people in vulnerable social positions have agency and may take action to resist vulnerability to disaster, for instance, by organizing mutual aid and strong social networks to share information and resources with neighbors (Jacobs, 2021; D. Z. Rivera, 2020).

Debates about Measuring Social Vulnerability

As noted, the national-level datasets SoVI and the SVI are perhaps the most widely used vulnerability measures in disaster research and practice, but there remains extensive debate, and doubt, about their construct validity (Bakkensen et al., 2017; Rufat et al., 2019; Spielman et al., 2020; Tate, 2012; Tellman et al., 2020). Vulnerability indices have typically been constructed using national datasets to represent social inequities across different contexts. The SVI combines 15 census variables—including poverty, unemployment, age, disability, language, minority status, housing, and transportation—to rank places by relative vulnerability. Despite progress in creating and testing social vulnerability indices, still not enough is known about the suitability of the components of the SVI for use beyond the continental United States for which it has primarily been developed. For instance, speaking English "less than well" may indicate higher vulnerability in some U.S. locations, but not necessarily in Puerto Rico. In locations where a vast majority of the population identifies as a racial or ethnic minority, as with Puerto Rico at more than 95% (U.S. Census Bureau 2022), this indicator of minority status may not be able to statistically differentiate between census tracts. The current study tests the external and structural validity of the SVI for Puerto Rico in terms of its ability to predict population loss after Hurricane Maria. Where possible, these findings could be used to improve the SVI and strengthen understanding of the differences between measures of vulnerability for the context of Puerto Rico relative to locations in the continental United States.

There have been promising examples of the SVI's ability to predict variation in post-disaster losses or requests for assistance. In a comparative test of various vulnerability indices used to predict outcomes after Hurricane Sandy in New York, Rufat et al. (2019) report a significant relationship between the SVI measure and the number of FEMA Individual Assistance applications as a proportion of the population in each census tract. Vulnerability indices have also been used to demonstrate disparities in short-term disaster assistance (Drakes et al., 2021); to examine procedural equity in the provision of disaster aid (Domingue & Emrich, 2019); and by federal emergency management teams in the wake of multiple hurricanes and floods (Cutter & Emrich, 2017).

Despite successful tests of the SVI, the validity of social vulnerability indices has been questioned in several cases (Bakkensen et al., 2017; Gall, 2007; Rufat et al., 2019; Spielman et al., 2020; Tellman et al., 2020). Rufat and colleagues (2019) assessed the construct, or empirical, validity of various indices by evaluating their explanatory power after Hurricane Sandy. They found that the SVI had low construct validity in this context, and called for further evaluations of the SVI's validity in different post-disaster contexts. The current study aims to do so by assessing the external validity of the SVI based on its explanatory power relative to population change after Hurricane Maria. The structural validity is also tested to assess whether the individual vulnerability indicators correlate with the construct of interest in Puerto Rico (Messick, 1995).

Additional evaluations of social vulnerability indices have found that simplifying more than a dozen variables into a single number makes for easier interpretation, but it can also obscure the contributions of individual variables (Spielman et al., 2020). An alternative approach would involve simply communicating the covariance of individual vulnerability indicators (Spielman et al., 2020). Others have suggested that variable selection can be improved using qualitative methods and local expert opinions on social vulnerability (Jacobs, 2021; Schmidtlein et al., 2008).

Paulino and colleagues (2021) have moved the field in this direction by producing a novel social vulnerability index for Guam modeled after the SVI, which does not currently provide data for this U.S. territory. They consulted with local stakeholders about how to adapt the SVI to best represent the local context. Working with residents and public health experts led the researchers to use different data to represent minority status in Guam and to integrate locally produced public health data with U.S. Census data (Paulino et al., 2021). The authors took an innovative, participatory approach to selecting relevant vulnerability indicators for the Guam SVI, planning backward from the question of which characteristics would hinder one's response to a typhoon. From there, they identified variables on housing type, wireless connection, and a custom minority variable. Finally, they tested both the CDC SVI model and their locationspecific adjusted SVI and found that the custom SVI better aligns with other data and local knowledge of disadvantaged populations (Paulino et al., 2021).

Social vulnerability indices have been used to explore a few dimensions of Puerto Rico's recovery in the wake of Hurricane Maria. Szczyrba et al. (2021) used machine learning to quantify contributions of vulnerability to building damage. They found that the CDC's SVI in combination with a structural vulnerability index were the primary predictors of observed patterns in hurricane damage; however, they also found that the relative importance of the SVI as a predictor of damage decreased with model permutations (Szczyrba et al., 2021). They ultimately acknowledge weaknesses of traditional vulnerability measures for the context of Puerto Rico and call for the development of "a place-based methodology to create representative vulnerability indices" (Szczyrba et al., 2021, p. 10). In another study of recovery patterns in Puerto Rico, Sotolongo, Kuhl, and Baker (2021) compare an environmental justice index to electricity restoration rates, which varied dramatically between urban and rural areas months after the hurricane. The current study investigates the relationship between social vulnerability and post-disaster population change in Puerto Rico. It simultaneously seeks to evaluate and refine the SVI for Puerto Rico as a first step toward a representative SVI measure.

Environmental Migration and Disasters

A robust literature base explains how migration can serve as a form of climate adaptation. In a review of research on migration and environmental hazards, Hunter demonstrates that "environmental factors play a role in shaping migration decisions, particularly among those most vulnerable" (Hunter, 2005, p. 273). McLeman and Hunter (2010) frame disasters as sudden-onset climate events that are associated with distress migration, in which exposed populations may attempt to flee shortly before or after a hazard occurs. They describe the disparate effects of two hurricanes in the Caribbean that highlight “the important influence of underlying socioeconomic conditions on migration outcomes following extreme events” (McLeman & Hunter, 2010, p. 273). Thus, prior environmental migration research has identified an enduring relationship between preexisting social inequalities and post-disaster migration patterns (Hunter, 2005; Hunter et al., 2015).

After Hurricane Katrina in 2005, Fussell and colleagues (2010) studied the return of displaced residents to New Orleans based on race and socioeconomic status. They found that Black displaced residents returned at slower rates than white displaced residents because Black residents were more likely to have lived in floodplains and sustained greater damage to their homes. In later research, Fussell (2018) further illustrated how population recovery is linked to housing recovery processes. Although these studies characterize the return rates among displaced residents, data and logistical challenges have limited studies of displaced residents who do not return to the affected area (Fussell, 2018).

Only a few studies have statistically tested the relationship between social vulnerability indices and migration after disasters. Research after Hurricane Katrina examined the relationship between social vulnerability and large-scale out-migration from affected areas (Myers et al., 2008). Using the SoVI measure with data aggregated to the county level, the authors found a significant statistical relationship between social vulnerability and post-hurricane out-migration by county. This relationship was spatially dependent with clustering of out-migration and social vulnerability around densely populated urban areas (Myers et al., 2008). This example is the closest comparison to the current study’s use of the SVI measure at the smaller census tract scale. Census tracts are spatial units of different sizes depending on population density, with average populations of about 4,000. Hunter and colleagues (2021) call attention to the importance of temporal and spatial scales for understanding relationships among climate vulnerability, environment, and health.

In a similar study after Hurricane Katrina, Elliott and Pais (2010) created a four-variable vulnerability index at the census tract level of analysis and argued that population redistribution after disaster varies between rural and urban areas. They found that the displacement hypothesis applies in urban areas, where vulnerable people are displaced from the hardest hit locations and replaced by wealthier people or businesses due to forces similar to gentrification. They also argued that the concentration hypothesis applies in rural areas, where vulnerable people become concentrated in the most affected locations after disaster because those with greater means migrate elsewhere. In Puerto Rico, the concentration hypothesis would suggest that those who left the most affected areas could afford to, and those who remained could not afford to leave. Credit bureau data has shown that out-migration from Puerto Rico remained elevated for census tracts with higher proportions of substandard housing (DeWaard et al., 2020). Facebook data indicated that the population of post-disaster migrants from Puerto Rico to the mainland U.S. was disproportionately male and from younger age groups, suggesting that more vulnerable populations remained in place (Alexander et al., 2019). Twitter data was also used to track population mobility after the hurricane, with nearly 4% of the resident sample still displaced nine months later (Martín et al., 2020). These prior studies may help explain the movement of people away from socially vulnerable areas after Hurricane Maria, including the movement of people from rural to urban areas as observed by Acosta et al. (2020).

Setting: Puerto Rico after Hurricane Maria

This study examines social vulnerability across Puerto Rico as a factor in post-disaster population change after Hurricane Maria in 2017. Disaster recovery has previously been assessed in Puerto Rico by examining population change and school closures (Hinojosa et al., 2019) as well as the time elapsed before electricity restoration in different Puerto Rican communities (Román et al., 2019; Sotolongo et al., 2021). Hurricane Maria provides an important opportunity to evaluate the components typically used in the United States to measure social vulnerability in the context of Puerto Rico, which differs demographically from the U.S. mainland in key ways, including a high overall poverty rate of 43.5%, double that of any other state (U.S. Census Bureau 2022). To improve broader understanding and measures of social vulnerability in different contexts, it is useful to investigate the extent to which the SVI is associated with observed disaster outcomes in Puerto Rico, such as population loss.

The conversation about population loss in Puerto Rico after Hurricane Maria became contentious due to discrepancies between the low death toll of 64 that was initially reported by the government and the higher number of deaths observed by hospital workers and emergency responders in the week after the storm (Santos-Burgoa et al., 2018; Santos-Lozada & Howard, 2018). This controversy about the apparent suppression of official death statistics prompted an independent group of researchers to estimate the death toll using a variety of data sources, including hospital records and measures of excess deaths in 2017 compared to the previous year (Santos-Lozada & Howard, 2018). After that study was published and reported by major newspapers, the Government of Puerto Rico revised its official estimate of the death toll from 64 to 2,975 lives lost. This revised toll was based on another study commissioned by the Government of Puerto Rico (Santos-Burgoa et al., 2018), officially making Hurricane Maria one of the deadliest hurricanes in U.S. history. That study found that the risk of excess mortality was highest for those in socioeconomically vulnerable municipalities and among elderly men, specifically (Santos-Burgoa et al., 2018). A year after the hurricane, the poorest municipalities had a persistent elevated risk of excess death that was 60% higher than normal, whereas the risk of death was 22% higher than normal across all municipalities. However, another study found that direct excess deaths mainly occurred during the two months after the hurricane (Spagat & van Weezel, 2020).

In addition to the high death toll, there were also high levels of out-migration from Puerto Rico associated with the hurricane, estimated to be about 129,000 people by July 2018 according to ACS data (Acosta et al. 2020). In the decade preceding Hurricane Maria, there was an overall trend of net out-migration from Puerto Rico, but 2017 to 2018 saw a marked increase in the rate to four percent of the population (Acosta et al. 2020; Flores and Krogstad 2019). Out-migration rates were high among families with children due to the widespread closure of public schools, 65% of which occurred in rural areas (Hinojosa et al., 2019). Thus, school closures may have been one impetus for permanent migration by families with young children from rural areas to cities within or outside of Puerto Rico, further contributing to an aging population in the island's mountainous interior (Acosta et al., 2020). Note that estimates of out-migration vary based on the population data source (Caraballo-Cueto, 2020).

For various reasons, it is challenging to accurately disentangle mortality from out-migration by census tract in Puerto Rico for the period under study (F. I. Rivera, 2020). Robust estimates of the death toll from the hurricane range from 800 to 4,645 (Kishore et al., 2018; Santos-Burgoa et al., 2018; Santos-Lozada & Howard, 2018; Spagat & van Weezel, 2020). The highest mortality estimate is less than one-tenth of estimated total out-migration through mid-2018 (Hinojosa et al. 2019; Santos-Lozada and Howard 2018); thus, out-migration constitutes most of the overall population loss after Hurricane Maria. Despite the significant net out-migration associated with Hurricane Maria, there are no reliable individual-level data on internal migration between census tracts. Considering this data availability, I posit that fatalities and migration in the period after Hurricane Maria may be conceptualized as linked outcomes related to pre-existing social vulnerability. Therefore, population change is conceptualized and measured here as a single disaster outcome influenced by social vulnerability.

Data and Measures

Social Vulnerability Index for Puerto Rico (2016 and 2018)

As the independent variable in this analysis, I test the CDC's composite measure of social vulnerability, the SVI. The 2016 version of the SVI for Puerto Rico reflects conditions in the year before Hurricane Maria in September 2017. Compared to other available vulnerability measures for Puerto Rico, I am interested in evaluating the SVI because it reflects the federal government's official approach to social vulnerability measurement. The SVI data for Puerto Rico are represented on the first map in Figure 1 to show the distribution of social vulnerability.

(Figure 1 here)

The 2016 SVI is constructed at the census tract level for the United States using five-year data from the American Community Survey (ACS) for the years 2012-2016 (*CDC SVI Documentation 2016*, 2022). The SVI ranks census tracts relative to each other within each of the 50 states and Puerto Rico based on social vulnerability on a scale from 0 to 1, in which a higher SVI value indicates greater relative vulnerability and lower values indicate lower vulnerability. The CDC also publishes a national level index that ranks tracts across all 50 states, but notably, it excludes Puerto Rico. Census tracts in Puerto Rico (n=884) are subdivisions of the 78 *municipios* (municipalities), which are administrative units similar to counties or parishes.

The SVI is created for census tracts that have a nonzero population by combining 15 indicators of social vulnerability, using the following percentile-rank approach (Flanagan et al., 2011).

First, tracts are ranked for each of the 15 variables from highest to lowest, with the scale for per capita income reversed to align with theorized vulnerability. Then, a percentile rank is calculated for each variable at the tract level using the following formula:

$$\text{Percentile Rank} = (\text{Rank-1}) / (\text{N-1})$$

The composite SVI value for a tract is created by summing across the 15 ranked variables, then repeating the percentile ranking a final time (Flanagan et al., 2011). The same process is used to create four sub-indices based on theoretical subsets of social vulnerability, which are shown in the descriptive statistics in Table 1. The CDC also provides detailed documentation about the construction of the 2016 SVI alongside an option to download the SVI datasets for various years (*CDC SVI Documentation 2016*, 2022).

Population Change Data

To generate the dependent population change variable, I calculated the difference in population by census tract as estimated for July 1, 2016, and for July 1, 2018, using the Puerto Rico Community Survey data from the U.S. Census Bureau. These are the population estimates that are contained within the SVI datasets and used to construct the SVI at the census tract level. As shown in the summary statistics in Table 1, the average population change per tract is -4.01%, or a mean loss of 161 people per tract. This is consistent with the overall estimated population change in Puerto Rico one year after Hurricane Maria (Acosta et al., 2020; Flores & Krogstad, 2019). For the methods used in this study, it is important to note that population change is approximately normally distributed across the census tracts.

Control Variables

Following the model of previous SVI validation research, I controlled for the intensity of the natural hazard to better isolate the relationship between social vulnerability and population change (Bakkensen et al. 2017; Rufat et al. 2019). I approximated hazard intensity using the control variable *peak wind speed* in miles per hour (mph), which Szczyrba and colleagues (2021) found to be the hazard most highly correlated with structural damage. To do so, I downloaded geospatial data on observed peak wind speeds from the National Oceanic and Atmospheric Administration (NOAA). Then, I calculated a spatial average of the peak wind speed for each census tract, resulting in a single number to estimate the average peak wind speed across the tract during the hurricane, ranging from 73 mph to 170 mph (Figure 2). This would be an imperfect approximation of hazard intensity at the household level because it does not account for isolated strong wind gusts capable of producing localized damage. However, this control does allow for comparison of relative hazard intensity at the census tract scale, as this study requires. Although I do not control for rainfall, landslides, or flooding, these hazards were found to be less strongly correlated with building damage than wind speeds were at the census tract level (Szczyrba et al., 2021). Future work could attempt to control for the compound nature of such hazards during the hurricane. Finally, in addition to controlling for hazard intensity, I also controlled for baseline population in each census tract to enable the comparison of population change across tracts of different populations.

(Figure 2 here)

Methods

This study's methods were guided by dual research aims of comparing social vulnerability to population loss and evaluating the SVI measure for Puerto Rico. First, to assess whether the SVI predicted population change in Puerto Rico after Hurricane Maria, I conducted multiple ordinary least squares (OLS) regression using the SVI measure as the independent variable and population change as the dependent variable. I also controlled for hazard intensity (maximum wind speed) and population in each census tract. To understand relationships among the vulnerability indicators, I first calculated Pearson's correlations between each of the 15 indicators and the outcome variable, population change. Population under age 18 was the single variable most strongly associated with population change, which is likely related to the numerous school closures after the hurricane. This was followed by six regression models to test the relationship between variations on the SVI and population change. All models can be represented by the following general equation using the regressor variable method (Allison, 1990), where subscript *t* refers to the census tract level of analysis:

$$\textit{population change}_{t} = \beta_0 + \beta_1\, \textit{SVI}_{1t} + \beta_2\, \textit{windspeed}_{2t} + \beta_3\, \textit{baseline}_{3t}$$

The first model compares the overall SVI measure to population change, and the next four models use each of the four SVI themes, which are intended to measure a particular conceptual subset of social vulnerability. A change score was used as the outcome for its easier relative interpretability compared to a percentage point difference in population (Appendix). In all models, robust standard errors were estimated to account for potential heteroskedasticity.

With the goal of refining the SVI measure to be more relevant to the context of Puerto Rico, I conducted exploratory factor analysis with varimax rotation on the 15 vulnerability indicators in the 2016 SVI. Results suggested that multiple variables were uncorrelated with the primary factor loadings for Puerto Rico (<0.20), indicating low structural validity. Therefore, I dropped three variables: mobile homes, group quarters, and multi-unit dwellings. Although multi-unit dwellings was moderately correlated with the first factor loading (0.35), I dropped this variable because its directionality was opposite that of the other SVI indicators. It was also strongly positively correlated with per capita income (0.47), which is counter to the theorized relationship. Finally, I dropped two additional variables on theoretical grounds: minority status and limited English proficiency. Because the CDC's minority status variable includes Hispanic/Latinx ethnicity, it is not a valid measure in the majority-minority context of Puerto Rico. I also removed the limited English proficiency variable because it was intended to be a proxy for immigration status, but it does not have that meaning or relationship to vulnerability in Puerto Rico where Spanish is the primary language (Tormos-Aponte et al., 2021).

These changes reduced the total to 10 vulnerability indicators that are all correlated with the underlying latent traits. With these 10 variables I constructed a revised 2016 SVI for Puerto Rico (SVI-10) using the same method as the CDC's SVI, described in the Data and Measures section and below. Using Stata, each variable was first divided by the 2016 population per tract to account for different population sizes. Then, tracts were ranked from highest to lowest along each of the 10 variables, with the scale for per capita income reversed. Next, a percentile rank was calculated for each variable at the tract level. The SVI-10 was generated by summing across the 10 ranked variables for each tract, followed by repeating the percentile ranking. I then tested the external validity of the SVI-10 in a sixth OLS regression model to predict population change, as with the previous five models. This enabled a comparison of the SVI-10 to the original SVI for predicting post-disaster population change in Puerto Rico.

(*Table 1 here)*

Results

The SVI measures explain more of the variation in population change than is explained by any individual variable. The results of the first regression model between the overall SVI measure and population loss (see Table 2) were statistically significant and indicate that census tracts in Puerto Rico with highest social vulnerability lost nearly 141 more people, on average, than tracts with the lowest social vulnerability (controlling for baseline population and hazard intensity). In other words, a one-unit increase in the SVI (scaled from 0 to 1) is associated with an additional population loss of 140.9. This suggests that the tracts with the highest level of social vulnerability experienced a population loss of approximately 70 more people compared to tracts at the median.

The results of the next four regression models estimate the relationship between each of the four SVI themes and population change. Results indicate that there is a strong and significant negative relationship between Theme 1: Socioeconomic Factors and population loss, β=-136.6 at the p<.001 level. There is also a significant negative relationship when testing Theme 2: Household Composition and Disability (β=-77.13, p<.05) and Theme 4: Housing and Transportation (β=-84.84, p<.05) against population loss. However, Theme 3: Minority Status and Language is the exception; it is not a significant predictor of population loss in Puerto Rico.

Although the directionality of the relationship is the same as for the other models, the effect size is much smaller for Theme 3. The results of all regression models are displayed in Table 2.

(Table 2 here)

For the sixth and final regression model, I replaced the CDC's SVI with the new SVI-10 measure. Not only did the new streamlined measure still significantly predict population loss, but it also produced a slightly larger effect size in which the most vulnerable census tracts in Puerto Rico lost about 151 more people on average than the least vulnerable tracts ($p=.000$; $r^2=.051$). In other words, every 10% increase in social vulnerability was associated with an additional loss of 15 people, on average. As a percent change in population, there is a difference of about four percentage points between the most and least vulnerable census tracts (see Appendix). Additionally, the SVI-10 resulted in a slightly lower AIC value (12,814.9<12,816.1) and BIC value (12834< 12835.2) and a higher R-squared value (.051), suggesting a better fit and explaining more variation using fewer variables. These findings suggest that, as a starting point, the SVI-10 could serve as a more efficient and relevant measure of social vulnerability for Puerto Rico than the CDC's current SVI with 15 indicators, especially for predictions of population change.

Discussion and Conclusion

The results of these analyses demonstrate a significant relationship between social vulnerability and population change after Hurricane Maria at the census tract level. This is consistent with theories of social vulnerability and environmental migration. It also aligns with prior empirical research on vulnerability and post-disaster migration after Hurricane Katrina, which found that some measures of social vulnerability helped explain population loss at the county level (Myers et al., 2008). These results are meaningful in the context of Puerto Rico because the archipelago has experienced a population decline each year for the past decade amid an ongoing economic crisis, with anomalously high population loss after Hurricane Maria (Santos-Lozada et al., 2020). This study finds that the SVI and SVI-10 explain some of the variation in post-disaster population change across different communities in Puerto Rico. This raises additional questions about whether the observed relationship between social vulnerability and population change was similar in other years before the hurricane, and whether it has continued since then. Ideally, future research would also be able to distinguish among population loss from mortality, internal migration, and out-migration from Puerto Rico. The observed relationship between vulnerability and post-disaster migration also merits further qualitative inquiry to strengthen its theoretical foundation.

Aside from the relationship between the CDC's SVI and population change, tests of the four themes within the SVI point to key issues in using the current SVI to represent vulnerability in Puerto Rico. Critically, Theme 3 does not significantly predict population loss, whereas other components of the SVI do. This is likely explained by the collinearity between the minority status variable and the overall population measure for Puerto Rico, meaning nearly all residents bear this so-called "minority status." Research about the census variables for race and ethnicity highlights that Puerto Ricans are often dissatisfied with the options to self-identify based on predetermined categories, and their responses are changing over time (Godreau & Bonilla, 2021). Taken together, the existing indicators for minority status and language are not appropriate indicators of vulnerability within Puerto Rico. Acknowledging this, I removed the minority status variable from the SVI-10, but Tormos-Aponte and colleagues (2021) instead revised the minority status variable to include only relevant forms of minority status, including Black/African American, Asian/Asian American, Native American/Native Puerto Rican, while removing Hispanic/Latinx status. Future work might collaboratively reimagine how to represent minority status in Puerto Rico within the constraints of a social vulnerability index, similar to approaches taken to represent vulnerability in Guam (Paulino et al., 2021) and guided by principles for collaboration in disaster contexts (West et al., 2021).

Context-specific and inclusive approaches to measuring vulnerability are not currently the norm, but this study joins others in asserting the need for such measures. In Puerto Rico and many parts of the United States, the composition of the population cannot be easily reduced to the race and ethnicity variables in the SVI. For example, Montgomery and Chakraborty (2015) disaggregated the Hispanic variable by country-of-origin, finding that exposure to flood risk varied significantly *within* the standard Hispanic ethnicity category. Thus, social vulnerability analyses should attend to locally relevant differences within the population of interest. Attempts to measure social vulnerability should ideally be made in consultation with people who are represented by the data, and analyses should be informed by a critical understanding of how vulnerability is socially produced (Jacobs, 2021). Furthermore, construction of a more robust and relevant SVI measure for Puerto Rico should draw from vulnerability research by Puerto Rican scholars working in this area of study (e.g. Lugo, 2019; Mayol-García, 2020; Santos-Hernández et al., 2020). More context-specific and inclusive measures would also better align with the third, critical approach to vulnerability, which recognizes vulnerability as dynamic and situational.

The challenges of applying the current SVI to measure vulnerability in Puerto Rico demonstrate the importance of ensuring such measures are grounded in theory about disaster vulnerability specific to the study context. I argue that the inadequacy of the official SVI for representing the population in Puerto Rico is a form of data injustice, a reflection of the U.S. government's colonial control over the archipelago, which extends to data availability. These analyses call attention to the need to improve data availability and relevance for Puerto Rico at the federal level. In this study, I employed sociological theory and knowledge of the context from community-based work to remove extraneous indicators from the SVI and create the revised 10-variable SVI, which demonstrated a stronger statistical relationship with population loss. The SVI-10 has higher external and structural validity for predicting population change in Puerto Rico. Because the CDC already reports Puerto Rico's SVI data separately from the other 50 states, revisions could be made to these variables for Puerto Rico without affecting SVI data for other locations. In addition to updating the SVI, I echo the calls of other scholars for social vulnerability indices to be accompanied by clear explanations about what they may be expected to predict or measure (Bakkensen et al., 2017; Rufat et al., 2019). This would enable researchers to test and utilize them more effectively, and it would help practitioners decide whether and when to use such measures to inform their decisions.

Although these findings demonstrate a compelling relationship between social vulnerability and population loss, there are limitations to this approach. First, the SVI only explains a small amount of the overall variation in population change at the census tract level. This suggests that there are other factors that influenced the observed patterns of population change, such as those related to the built environment or gender disparities, which could be variables included in a future SVI measure. There is also evidence to suggest that social vulnerability may be associated with non-migration, as with trapped populations (Ayeb-Karlsson et al., 2018; Black & Collyer, 2014), which may have weakened the apparent relationship between the SVI and population change. Second, the population data used in the analyses only provide one number for *net* population change, meaning they do not indicate how many people may have moved to and away from each census tract nor do they distinguish between death and outmigration. For example, some urban census tracts had a net increase in population due to internal migration while still losing residents. Third, these regression models do not control for the extent of structural damage to homes in each tract, which prior studies have found to influence return migration (Fussell et al., 2010). The lack of rigorous data on the built environment in Puerto Rico is another area for continued research. Future studies should control for structural damage and other forms of disruption to the built and natural environment in relation to population change.

These limitations mainly highlight opportunities to build upon this work in the future. The results of this study demonstrate that social vulnerability is an important dimension of post-disaster population change and migration patterns after Hurricane Maria. It also makes a case for revising and improving the SVI for Puerto Rico by removing some of the current extraneous variables and by identifying context-specific vulnerability indicators. Considering Puerto Rico's recurring encounters with compound natural hazards, including earthquakes, hurricanes, floods, and landslides, the archipelago should have a more valid measure of vulnerability, which could help better support those with greatest needs before and after disaster.

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Figures and Tables

Figure 1

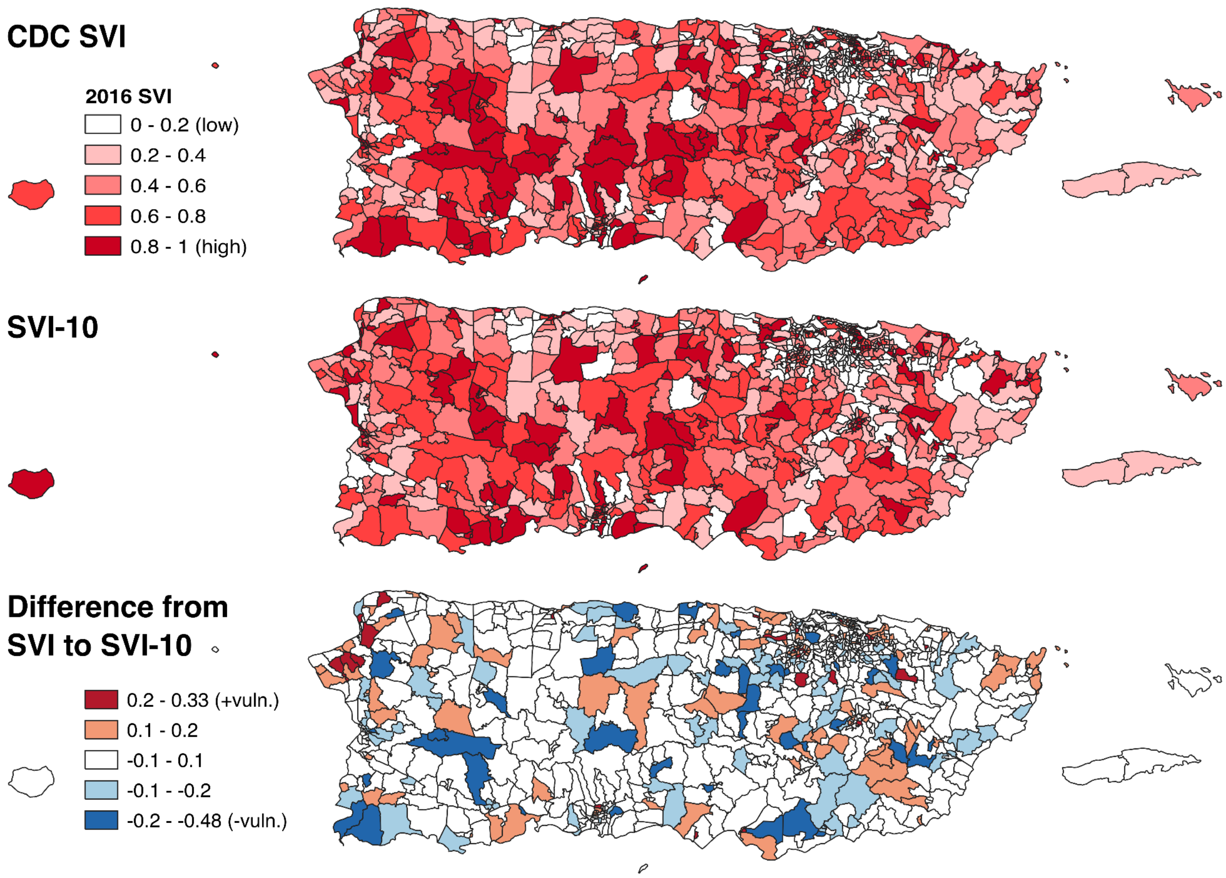

Fig. 1 The first two maps depict the 2016 CDC SVI and SVI-10, respectively, for census tracts in Puerto Rico. The darkest colors represent areas of highest vulnerability and white areas represent lowest vulnerability. The third map displays areas of greatest difference between the SVI and SVI-10. Red represents an increase in vulnerability, blue represents decreased vulnerability, and white represents a change of less than 0.1. (Source: Author, using data from the CDC and U.S. Census Bureau)

Figure 2

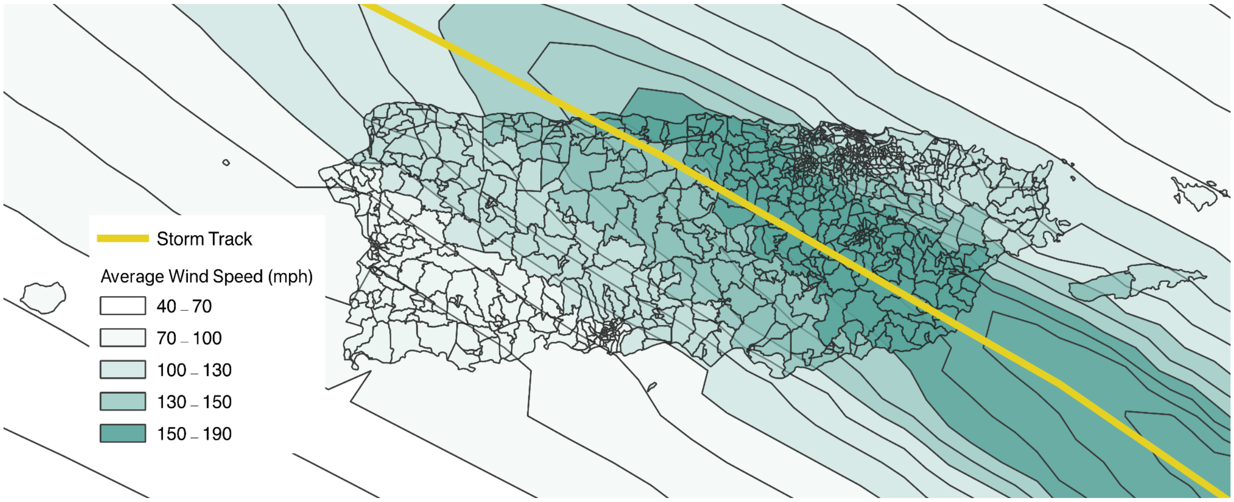

Fig. 2 Map depicting wind speeds across Puerto Rico's census tracts during Hurricane Maria. Darker colors represent stronger wind speeds. The thin yellow line represents the storm's center track from southeast to northwest on September 20, 2017. (Source: Author, using NOAA data)

Table 1: Descriptive Statistics for all Variables at the Census Tract Level

Variable (n=884)	Mean	SD	Min	Max
Population Change 2016-18	-161.08	347.79	-1559	1380
Percent Population Change 2016-18	-4.01	9.37	-38.70	68.81
Composite SVI Measures				
Overall Social Vulnerability Index (SVI)	0.5	0.29	0	1
SVI Theme 1: Socioeconomic	0.5	0.29	0	1
SVI Theme 2: Household Composition / Disability	0.5	0.29	0	1
SVI Theme 3: Minority Status / Language	0.5	0.29	0	1
SVI Theme 4: Housing / Transportation	0.5	0.29	0	1
15 Vulnerability Indicators				
Poverty	.4596	.1625	.0329	1.00
Unemployment	.0677	.0339	0	.2529
Per Capita Income (USD)	$11,629	6,584	1,681	57,092
No High School Diploma	.1815	.0758	.0082	.4483
Population under 18	.2117	.0571	.0227	.5023
Population 65+	.1835	.0562	.0198	.4123
Persons with a Disability	.2174	.0643	.0477	4101
Single Parent	.0510	.0246	.0026	.1842
Minority Population	.9919	.0162	.7471	1.00
Speaks Limited English	.5939	.1405	.0915	.9082
Population in Multi-Unit Dwellings (10+ units)	.0516	.1228	0	1.00
Mobile Homes Estimate	.0015	.0087	0	.2389
Crowding - Households with More People than Rooms	.0129	.0091	0	.0573
No Vehicle	.0691	.0496	.0025	.4023
Persons Living in Group Quarters	.0111	.0396	0	.6575
Control for Hazard Intensity				
Peak Wind Speed During Hurricane (mph)	130.81	23.39	73.30	170

Source: Data are from the CDC Social Vulnerability Index for 2016 and 2018, which include the U.S. Census Bureau Puerto Rico Community Survey 5-year population estimates for 2012-2016 and 2014-2018. Each vulnerability indicator is calculated as proportion of the population in each census tract. Per capita income is calculated as the average in each tract.

Table 2: Results of OLS Regression between SVI and Population Change by Tract

Variables	(1) Orig. SVI	(2) SVI Theme 1	(3) SVI Theme 2	(4) SVI Theme 3	(5) SVI Theme 4	(6) SVI-10
SVI Measure	-140.9***	-136.6***	-77.13*	-46.72	-84.84*	-150.6***
	(37.94)	(38.67)	(36.65)	(39.42)	(38.39)	(37.92)
Windspeed	0.262	0.137	0.451	0.441	0.361	0.256
	(0.514)	(0.517)	(0.515)	(0.516)	(0.516)	(0.514)
Baseline Population	-0.0407***	-0.0399***	-0.0385***	-0.0372***	-0.0385***	-0.0431***
(e_totpop)	(0.00805)	(0.00801)	(0.00806)	(0.00806)	(0.00818)	(0.00814)
Constant	37.33	48.58	-28.05	-46.93	-12.26	52.42
	(76.13)	(77.42)	(72.92)	(71.54)	(77.95)	(77.61)
N	884	884	884	884	884	884
R^2	0.050	0.049	0.041	0.038	0.042	0.051
adj. R^2	0.047	0.046	0.037	0.035	0.038	0.048
AIC	12816.1	12816.9	12824.5	12826.9	12823.7	12814.9
BIC	12835.2	12836.1	12843.7	12846.0	12842.9	12834.0

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Data are from the CDC Social Vulnerability Index for 2016 and 2018, which include the U.S. Census Bureau Puerto Rico Community Survey 5-year population estimates for 2012-2016 and 2014-2018.

Appendix A

Below is an alternative to this article's regression models with percent change in population as the dependent variable instead of absolute population change, which was used in the main text for better interpretability. The level of significance for all models is consistent with those in Table 2. For the SVI-10 model, the most vulnerable tracts experienced a population loss 3.98 percentage points greater than that of the least vulnerable tracts, on average. The general equation for the following six models is:

$$\textit{percent change}_t = \beta_0 + \beta_1\, SVI_{1t} + \beta_2\, \textit{windspeed}_{2t}$$

Table 3: Results of OLS Regression between SVI and Percent Population Loss by Tract

Variables	(1) Orig. SVI	(2) SVI Theme 1	(3) SVI Theme 2	(4) SVI Theme 3	(5) SVI Theme 4	(6) SVI-10
SVI Measure	-3.723**	-3.606**	-2.292*	-1.040	-2.144*	-3.984***
	(1.143)	(1.192)	(1.035)	(1.155)	(1.061)	(1.119)
windspeed	0.00507	0.00200	0.0108	0.0107	0.00841	0.00421
	(0.0131)	(0.0133)	(0.0130)	(0.0130)	(0.0131)	(0.0132)
Constant	-2.815	-2.472	-4.281*	-4.894**	-4.042*	-2.572
	(1.904)	(1.961)	(1.800)	(1.783)	(1.876)	(1.906)
N	884	884	884	884	884	884
R^2	0.014	0.013	0.006	0.002	0.005	0.016
adj. R^2	0.011	0.010	0.003	-0.001	0.003	0.013
AIC	6457.0	6457.9	6464.2	6467.7	6464.7	6455.3
BIC	6471.3	6472.3	6478.5	6482.0	6479.1	6469.7

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$