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Social Vulnerability Assessment of Gulf Coast States

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The social vulnerability of the Gulf Coast states—Texas, Louisiana, Mississippi, Alabama, and Florida—is rapidly increasing due to a complex interplay of social, environmental, and economic factors. These include climate change, extreme weather events, sea level rise, land subsidence, social inequalities, aging infrastructure, urbanization, population growth, and economic shifts. This paper aims to assess the social vulnerability of these states through a comprehensive analysis of socio-economic and demographic factors, utilizing the Social Vulnerability Index (SVI) as a framework. Key indicators for the SVI encompass population, age, race, education, housing structure, income, and disability. To evaluate the relative significance of these indicators, the Principal Component Analysis (PCA) method was implemented, and the variables were categorized into distinct groups for a more nuanced assessment of vulnerability. Subsequently, the SVI for each of the five states adjacent to the Gulf of Mexico was calculated, and their vulnerabilities were analyzed and compared. The results will assist decision-makers in effectively planning for both pre-disaster preparedness and post-disaster recovery in these disaster-prone regions.

Keywords: Vulnerability Assessment, Sustainable Built Environment, Gulf of Mexico, Socioeconomic Status

Introduction

The convergence of rapid population growth, urbanization, and shifting climate patterns has exacerbated vulnerability to natural hazards. Proximity to bodies of water, such as oceans, seas, and gulfs, further elevates the risk of such hazards (Rouhanizadeh et al., 2024). A natural hazard becomes a natural disaster when it directly or indirectly impacts human populations, leading to loss of life or property (Moller-Jenson et al., 2022; Safapour et al., 2023). The coastal region of the Gulf of Mexico, situated near the Atlantic Ocean, has historically experienced a high susceptibility to natural disasters like storms and floods. While complete prevention of natural disasters may be unattainable, vulnerability assessments, hazard mitigation strategies, and emergency management plans can significantly mitigate their impacts and accelerate recovery efforts (Frigerio et al., 2016; Safapour, 2020; Rouhanizadeh, 2020).

A comprehensive risk and impact assessment requires a vulnerability assessment that encompasses both traditional physical and environmental factors and emerging social, economic, and demographic variables (Cutter et al., 2006). Physical and environmental factors, including topography, soil composition, existing infrastructure, and climate patterns, significantly influence a region's susceptibility to natural hazards. However, it is equally essential to consider dynamically changing factors such as population density, disability, income levels, age distribution, and financial stability, which are core social, economic, and demographic variables. These factors impact a community's capacity to anticipate, manage, withstand, and recover from the consequences of natural hazards and should be incorporated into effective disaster preparedness, recovery, and response strategies.

Historical evidence consistently demonstrates that marginalized populations disproportionately bear the brunt of natural disasters. The evacuation failures during Hurricane Katrina, affecting over 250,000 individuals in New Orleans, were largely attributable to resource limitations rooted in socioeconomic disparities (Cutter et al., 2006). This underscores the imperative to enhance assessment methodologies by integrating socioeconomic and demographic factors related to social vulnerability into decision-making and emergency management processes (Cutter et al., 2012).

The present study examines socioeconomic and demographic factors to assess vulnerability within the five Gulf Coast states: Texas, Louisiana, Mississippi, Alabama, and Florida. These states serve as a valuable case study due to their diverse communities, high exposure to natural hazards, economic significance, environmental importance, historical context, governance challenges, and relevance to broader climate change discussions (Rouhanizadeh & Safapour, 2024). The present study considers factors such as income, age, race, education, housing structure, disability, and population, as these socioeconomic and demographic variables reflect existing societal inequalities.

Literature Review

Studies consistently identify marginalized populations as particularly vulnerable to the impacts of natural disasters. Low-income individuals, the elderly, children, persons with disabilities, and minorities often experience disproportionate impacts (Collins et al., 2018). Cutter et al. (2006) emphasized the heightened susceptibility of areas with high population density, a significant elderly population, and a prevalence of low-income households to the consequences of natural disasters, such as floods. The authors further noted that women may face unique challenges during disaster recovery due to family responsibilities and lower wages. Consequently, Cutter et al. (2006) advocated for the inclusion of socially vulnerable groups in risk assessments to ensure that disaster preparedness and response measures are equitable and inclusive.

Researchers have conducted comprehensive assessments of flood vulnerability using a variety of data sources, including census data, remote sensing imagery, geographic information systems (GIS), and machine learning techniques. These resources have provided valuable insights into demographic and socioeconomic aspects at various spatial scales. Additionally, experts have employed a range of statistical and modeling techniques, such as multi-criteria analysis, spatial analysis, and vulnerability indices, to measure and incorporate these elements into thorough evaluations of flood vulnerability (Hamidi et al., 2020).

Several research studies have specifically evaluated flood vulnerability in distinct coastal areas of the United States (Cutter et al., 2006). For example, in the aftermath of Hurricane Katrina in the Gulf Coast region, researchers emphasized the significant role of socioeconomic factors, such as poverty levels and educational attainment, in influencing vulnerability to flooding (Finch et al., 2010). However, a substantial research gap persists regarding comprehensive assessments of flood hazards in vulnerable contexts that are more directly relevant to community needs (Frigerio et al., 2016; Safapour et al., 2021). Existing studies on flood hazard zonation have primarily focused on the physical vulnerability of floods using a pixel-based approach (Kwak 2017). While these studies accurately identify potential flood hazard areas, they often lack integration of socioeconomic data, community resilience, and adaptive capacity in flood risk evaluation. Furthermore, the Gulf Coast states share interconnected climatic exposure and economic systems, particularly with respect to recurrent hurricanes and coastal flooding. By comparing these states together, organizations like FEMA, NOAA and the Gulf Coast Ecosystem Restoration Council can clearly see which areas are more vulnerable. This big picture helps them to make informed prioritization of funding, equitable resource allocation, and coordinated resilience planning across the Gulf Coast.

Research Methodology

The present study focuses on a comprehensive assessment of social vulnerability within the five states adjacent to the Gulf of Mexico: Texas, Louisiana, Mississippi, Alabama, and Florida. To complete this study, the research methodology consists of the following steps: selection of relevant indicators, the data collection and pre-processing methodologies, the framework for social vulnerability assessment, and the computation of SVI. Figure 1 presents the process of research methodology.

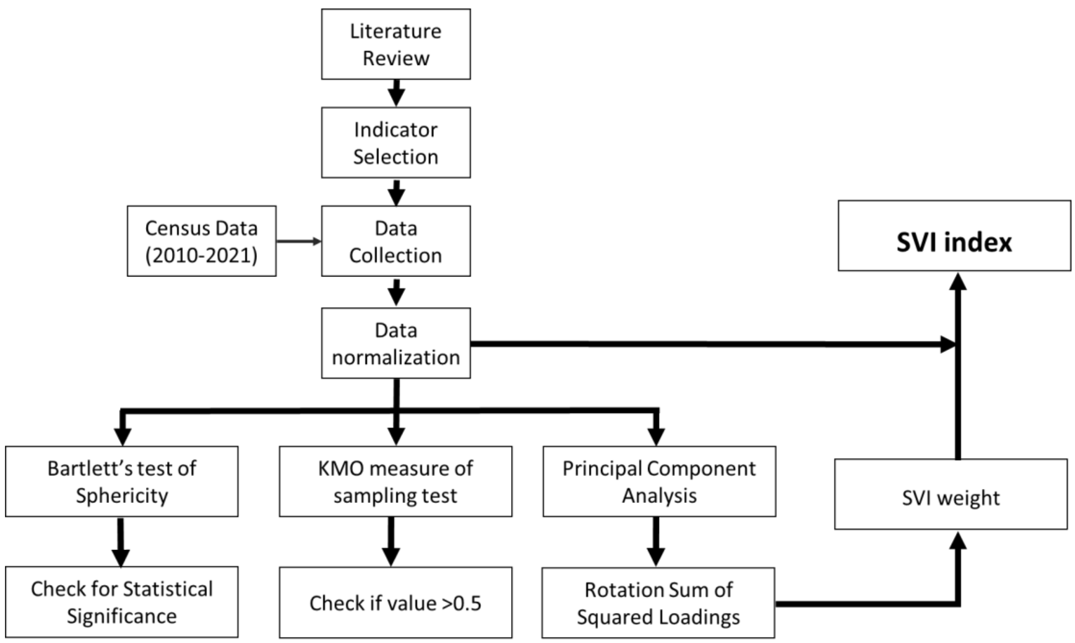

Figure 1. Research methodology

Literature Review

A comprehensive literature review was conducted to gather recent articles published between 2005 and 2024. Various search engines, including Google Scholar, Web of Science, Science Direct, ResearchGate, and libraries of renowned publishers like the ASCE library, were utilized for this purpose. The initial search employed a range of keywords and keyword combinations such as "social vulnerability," "Gulf of Mexico," "vulnerability assessment," "socioeconomic status," and "vulnerability indicator," resulting in the collection of 72 sources, including journal articles, conference papers, books, and research reports related to social vulnerability assessments of the Gulf Coast. The dataset was then narrowed to academic and scientific publications within the specified time frame (2005 to 2024) and further refined to include only those articles most relevant to the study's objectives. Ultimately, 46 manuscripts that aligned with the research goals and criteria were selected, and their metadata was downloaded using the Mendeley reference management software.

Indicator Selection

Coastal vulnerability is a complex construct characterized by a positive correlation with coastal hazards and social vulnerability (Cardona et al., 2012). The selection of indicators for this study was informed by socioeconomic and demographic data. Through a comprehensive literature review, seven key indicators were identified: population, age, race, education, housing structure, income, and disability. These indicators are a combination of factors synthesized from Cutter et al. (2006, 2012) and additional insights from our comprehensive literature review. As presented in Table 1, within these indicators, ten specific variables were chosen to elucidate the socioeconomic conditions that impact a community's preparedness, response, and recovery capabilities in the face of hazards and disasters (Frigerio et al., 2016). These variables may exert both positive and negative influences, depending on whether they amplify or mitigate social vulnerability.

Table 1. Indicators contributing to social vulnerability

Indicator	Definition	Impact on SV	Source
Population	Population density- Total population divided by land area (persons per sq. mile/km²)	Increase	Zhang and You (2014)
	Below poverty line	Increase	Park and Xu (2022)
	Minority	Increase	Flanagan et al. (2011)
Age	Proportion of population under age 5 and age 65+	Increase	Cutter et al. (2012)
Income	Households with income less than the median income	Increase	Zhang and You (2014)
Disability	Percentage of civilian non-institutionalized population reporting difficulty in ≥1 of 6 functional domains (hearing, vision, cognition, ambulation, self-care, independent living)	Increase	Hadipour et al. (2020)
Housing Structure	Renter-occupied housing unit	Increase	Tasnuva et al. (2021)
	Mobile housing units	Increase	Flanagan et al. (2011)
Education	High school graduates and those with less than a high school education	Increase	Bucherie et al. (2022)
Race	Minority Percentage of persons identifying as non-White and/or Hispanic/Latino	Increase	Cutter et al. (2012)

Description of Variables

The U.S. Census Bureau defines *below poverty line* as the poverty thresholds, which vary by household size and number of children and represent limited financial capacity to prepare for and recover from disasters. Similarly, *low-income households* were defined as those earning below the typical median income, reflecting economic fragility that increases recovery challenges (Flanagan et al., 2011; Cutter & Emrich, 2017; Collins et al., 2018). *Age vulnerability* included children under five and adults aged 65 or older, as these groups often require additional support during emergency response and may have limited mobility and resources (Frigerio et al., 2016).

The *disability* term was measured according to ACS survey definitions which classifies them into six disabled categories if they report serious difficulty in one or more functional domains such as hearing, vision, cognition, ambulation, self-care, or independent living ((CDC), 2022). Race and disability-related vulnerability in this study does not stem from identity itself, but rather it comes from historic underrepresentation, discrimination, and reduced access to services, which can amplify during the disaster (Cutter & Emrich, 2017). Similarly, gender-related vulnerability reflects the influence of socio-economic structures rather than characteristics inherent to women. Report by International Bank for Reconstruction and Development and The World Bank (2021) shows women may experience disproportionate impacts due to wage disparities, caregiving burdens, and limited access to resources before and after disasters. Societal constructs, male centric community makes females more vulnerable so need special consideration (Cutter & Emrich, 2017).

Data Collection and Pre-Processing

This study uses socioeconomic and demographic data obtained from the United States Census Bureau's American Community Survey (ACS) from 2010 to 2021 for the five Gulf Coast states: Texas, Louisiana, Mississippi, Alabama, and Florida. The ACS provides annually updated statistics for all U.S. states and offers the most reliable small-area data for vulnerability assessment. All variables used in the SVI were extracted from ACS detailed tables and presented in Table 1. The search filter option was used to extract data from online portal of U.S. Census Bureau for all the 10 indicators such as age, race, education, housing, income, and some other things. Considering the diverse units of the data, standardization was necessary. To achieve a common scale, a standard Z-score normalization was applied using Equation 1, where x represents the data value, μ is the sample mean, and σ is the sample standard deviation. This pre-processing step transformed the data distribution to have a mean of 0 and a standard deviation of 1.

$$z = \frac{x - \mu}{\sigma} \qquad \text{Equation 1}$$

Statistical Analysis

The standardized data represents various socioeconomic and demographic indicators. To assess social vulnerability in the five states adjacent to the Gulf of Mexico, a statistical analysis was conducted using PCA. Prior to applying for PCA, the Keiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were employed to evaluate sample adequacy. IBM SPSS Statistics 28 was utilized for the PCA, KMO test, and Bartlett test. The primary objective of PCA is to reduce the dimensionality of the variables while preserving as much information as possible by transforming the original variables into a new set of uncorrelated variables known as principal components. These principal components (PCs) are linear combinations of the original variables and are ranked according to their explained variance. Due to their ability to capture high variance in a few components, PCA can be used to identify the importance of each variable using only a subset of components. In this study, four PCs were extracted, collectively explaining approximately 81% of the total variance.

For each principal component, the strength and direction of the relationship between the original variables and the derived principal components were calculated, a measure referred to as "loading." In factor analysis, the "rotated component matrix" was utilized, providing the loadings for the rotated components. This simplifies the interpretation of the components by aligning them more directly with the data (Wu, 2021).

Social Vulnerability Index

The weights associated with each rotated component matrix for the four principal components are combined to form a variable weight by considering the variance explained by each PC, as shown in Equation 2. The overall SVI for each state is calculated using the original standardized data and the variable weights, as outlined in Equation 3.

$$\text{SV weight}_{\text{n}} = \frac{(\text{Component loading}_{\text{n}} \text{ x percentage of variance}_{\text{n}})}{\text{total variance}} \qquad \text{Equation 2}$$

$$\text{SVI}_{\text{i}} = \sum_{\text{n}=1}^{\text{m}} \text{SVI weight}_{\text{n}} \text{ x normalized}_{\text{data}_{\text{i,n}}} \qquad \text{Equation 3}$$

where *i* represents the number of states, *n* denotes the different PCs, and *m* indicates the total number of PCs.

Results

To investigate the SVI of the five focused states- Texas, Louisiana, Mississippi, Alabama, and Florida- using ten variables and PCA, the KMO measure of sampling adequacy and Bartlett's test of sphericity were conducted. A KMO value of 0.67, combined with a statistically significant result from Bartlett's test of sphericity (Approximate Chi-Square = 412.991, Degrees of Freedom (df) = 45, Significance (p-value) <0.001), was obtained. A KMO value greater than 0.5 indicates a moderate level of sampling adequacy for factor analysis, while a *P*-Value of less than 0.005 for Bartlett's test of sphericity confirms that the variables in the dataset are not independent (i.e., statistically significant), supporting the use of factor analysis to explore factor importance (Safapour et al., 2021).

In PCA, SV weighting determines the influence of variables on the principal components (PCs), shaping the analysis of vulnerability patterns. Negative loading values indicate an inverse relationship, where higher values of certain variables decrease the vulnerability represented by the component. A higher SV weight emphasizes the importance of specific variables, potentially altering the interpretation of components and guiding the identification of vulnerable populations or areas, which is critical for informed decision-making and policy development.

Table 2 presents the results of each variable, and their loadings based on the rotated component matrix for the four principal components, which are identified as Quality of Life, Housing and Diversity, Inclusivity, and Income. Together, these four principal components account for approximately 81% of the total variance. The criteria for computing factor loadings were established as greater than 0.5 or less than -0.5 (Cutter & Emrich, 2017; Safapour et al., 2022).

As shown in Table 2, low-educated populations, renter-occupied housing units, and Minority gender exhibited the highest contributions to their respective principal components, receiving the highest loading factors. Notably, low-income households were the sole variable contributing to the fourth principal component (income). The last column in Table 2 displays the SV weight of each variable, calculated using Equations 2 and 3. Table 2 identifies Quality of Life as the principal component with highest weight, influencing the social vulnerability of coastal communities. This component plays a pivotal role, as lower quality of life can hinder communities' ability to address and recover from various disasters. Educational disparities often lead to limited awareness and understanding of disaster risks. Mobile housing units in vulnerable areas are susceptible to structural damage and displacement, with limited escape routes. Moreover, high population density increases the number of individuals at risk, straining emergency services and complicating evacuation efforts.

Table 2. Results of PCA

#	Variable	Component Loading				Principal Component	SV weight
		PC1	PC2	PC3	PC4		
1	Low-educated population	0.946				Quality of Life	0.443
2	Mobile housing units	0.849					0.398
3	Low-income populations	0.805					0.377
4	Children and the elderly	-0.945					-0.443
5	Population density	-0.685					-0.321
6	Renter-occupied housing units		0.833			Housing and Diversity	0.181
7	Minority race		-0.853				-0.186
8	Minority gender			0.819		Inclusivity	0.142
9	Disabled population			-0.682			-0.118
10	Low-income households				0.939	Income	0.131
Rotation Sum of Squared Loadings							
Total Variance Explained (VE)		3.789	1.765	1.402	1.129		
Percentage of Variance (%)		37.886	17.654	14.018	11.286		
Cumulative percentage of VE (%)		37.886	55.541	69.559	80.848		
Kaiser–Meyer–Olkin Measure of Sampling Adequacy						0.67	
Bartlett's test of Sphericity							
Approximate Chi-Square						412.991	
Degree of freedom						45	
Significance						0.000	

As presented in Table 2, Housing and Diversity is another principal component responsible for increasing social vulnerability in the Gulf Coast region. Housing and diversity influence social vulnerability by affecting the availability of resilient housing options, exposure to environmental risks, and the equitable distribution of resources among people of different races and ethnicities.

Finally, the SVI was calculated for each focused state using the SVI weights and standardized (z-score) data of each variable, as outlined in Equation 3. The final result of the PCA (i.e., the SVI value) is relative and is based on census data from 2010 to 2021. It has been scaled to comparable quantities by normalizing them to the z-scale, as described in Equation 1. The index can be used only to compare the five states adjacent to the Gulf of Mexico, which is the scope of this study. The PCA weights are derived from the variance structure of these five states. They can be generalized to other U.S. regions only after the PCA is re-estimated. The results for the focused states are presented in Figure 2. As shown in Figure 2, Alabama and Florida exhibited the highest social vulnerability, followed by Texas. Louisiana demonstrated a lower social vulnerability than Alabama, Florida, and

Texas based on socioeconomic and demographic factors. In contrast, Mississippi was found to be the least socially vulnerable, with the lowest SVI score among the five states.

As depicted in Figure 2, Alabama and Florida, two contiguous states, exhibit comparable social vulnerability scores, followed by Texas and Louisiana, respectively. Mississippi, situated along the Gulf Coast, demonstrates the lowest social vulnerability among the five states based on socioeconomic conditions. These rankings are paramount for the development of targeted and effective strategies to bolster resilience, mitigate disparities, and ensure that vulnerable populations receive the requisite support during and after disasters. Such an approach contributes to the creation of more sustainable and equitable communities in the face of climate-related challenges. An understanding of these vulnerability rankings can inform policymakers, researchers, and community leaders in the allocation of resources, the implementation of policies, and the development of strategies to address the specific social vulnerabilities in each region. This analysis underscores areas that may necessitate increased attention and assistance to enhance resilience and reduce vulnerability.

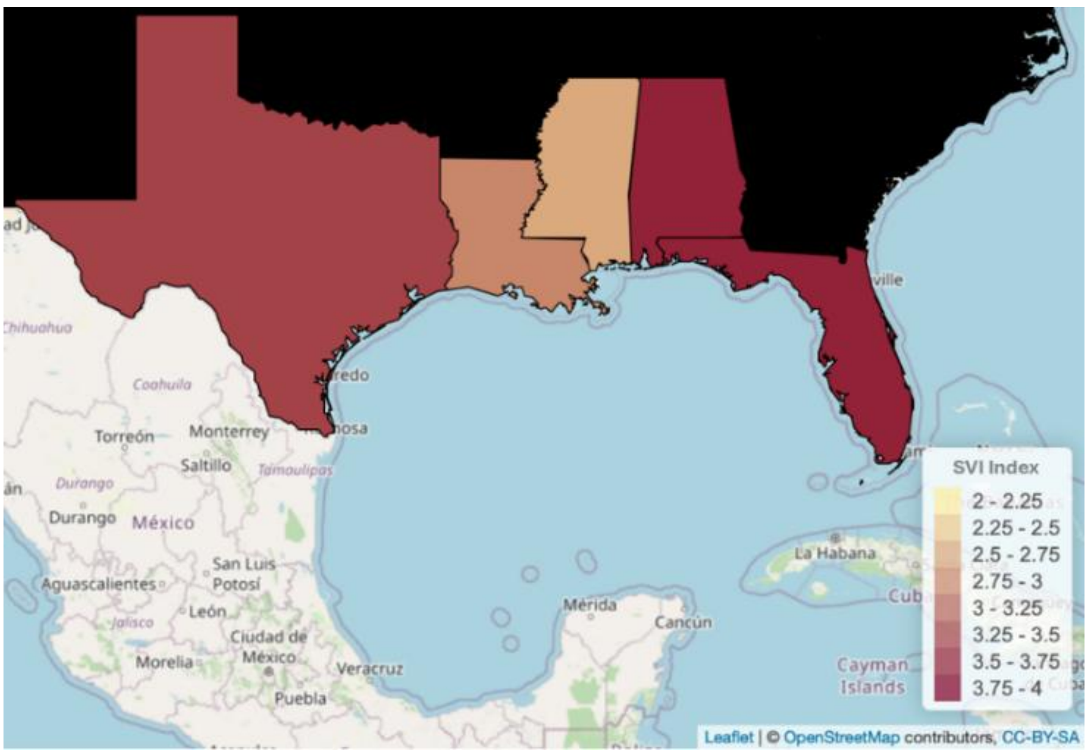

Figure 2. Vulnerability assessment results

Conclusions

The primary objective of this paper is to elucidate the significance of social vulnerability assessments in addressing the challenges confronting vulnerable communities during disasters. The vulnerability assessment for five states adjacent to the Gulf of Mexico—Texas, Alabama, Louisiana, Mississippi, and Florida—utilizes the SVI to facilitate the prioritization of resources, the development of emergency plans, the enhancement of community resilience, the promotion of equitable recovery, and the support of policy development. The calculated SVIs of these states reveal that Alabama and

Florida exhibit the highest social vulnerability, followed by Texas. Louisiana demonstrates lower vulnerability than Alabama, Florida, and Texas, while Mississippi possesses the lowest social vulnerability. These social vulnerability rankings serve as valuable tools for identifying regions that may require increased attention and assistance. By allocating resources and support to the most vulnerable communities, it is possible to strengthen these areas and improve their preparedness for future challenges. This study is limited by its state-level scale, use of a relative SVI measure, reliance solely on socioeconomic indicators, and single-year ACS dataset. The Future work should explore county-level analysis, integrating multi-hazard risk layers such as flooding, hurricane and assess its temporal changes.

References

Cardona, O. D., Van Aalst, M. K., Birkmann, J., Fordham, M., Mc Gregor, G., Rosa, P., ... & Thomalla, F. (2012). Determinants of risk: exposure and vulnerability. In *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change* (pp. 65-108). Cambridge University Press.

Collins, T. W., Grineski, S. E., & Chakraborty, J. (2018). Environmental injustice and flood risk: a conceptual model and case comparison of metropolitan Miami and Houston, USA. *Regional environmental change*, *18*, 311-323.

Cutter, S. L., Emrich, C. T., Mitchell, J. T., Boruff, B. J., Gall, M., Schmidtlein, M. C., ... & Melton, G. (2006). The long road home: Race, class, and recovery from Hurricane Katrina. *Environment: Science and Policy for Sustainable Development*, *48*(2), 8-20.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2012). Social vulnerability to environmental hazards. In *Hazards vulnerability and environmental justice* (pp. 143-160). Routledge.

Cutter, S. L., & Emrich, C. T. (2017). Social vulnerability index (SoVI®): Methodology and limitations. *Columbia, SC: Hazards and Vulnerability Research Institute*, 1-6.

Finch, C., Emrich, C. T., & Cutter, S. L. (2010). Disaster disparities and differential recovery in New Orleans. *Population and environment*, *31*, 179-202.

Frigerio, I., Ventura, S., Strigaro, D., Mattavelli, M., De Amicis, M., Mugnano, S., & Boffi, M. (2016). A GIS-based approach to identify the spatial variability of social vulnerability to seismic hazard in Italy. *Applied geography*, *74*, 12-22.

Hamidi, A. R., Wang, J., Guo, S., & Zeng, Z. (2020). Flood vulnerability assessment using MOVE framework: A case study of the northern part of district Peshawar, Pakistan. *Natural Hazards*, *101*, 385-408.

International Bank for Reconstruction and Development and The World Bank. (2021). Gender Dimensions of Disaster Risk and Resilience.

Kwak, Y. J. (2017). Nationwide flood monitoring for disaster risk reduction using multiple satellite data. *ISPRS International Journal of Geo-Information*, *6*(7), 203.

Rouhanizadeh, B., & Safapour, E. (2024). A MAP-based approach to identify the social vulnerability to flood hazard in states adjacent to Mexican Gulf. *International Journal of Disaster Risk Reduction*, *111*, 104717. https://doi.org/10.1016/j.ijdrr.2024.104717

Rouhanizadeh, B., Safapour, E., & Silwal, A. (2024). A GIS-Based Social Vulnerability Assessment of Communities in Coastal Areas Exposed to Extreme Flood Events: A Case Study of the New Orleans Urban Area. *Proceeding in ASCE Construction Research Congress,* Des Moines, Iowa, March 20-23, 2024, (pp. 610-619). https://doi.org/10.1061/9780784485279.061

Safapour, E. (2020). *A Decision Support System for Success of Post-Hurricane Reconstruction of Transportation Infrastructures* (Doctoral dissertation, The University of Texas at Arlington).

Rouhanizadeh, B. (2020). *Analysis of barriers causing delay in post-hurricane recovery: Experts' vs. public's perspectives* (Doctoral dissertation, The University of Texas at Arlington).

Safapour, E., Kermanshachi, S., & Kamalirad, S. (2021). Analysis of effective project-based communication components within primary stakeholders in construction industry. *Built Environment Project and Asset Management*, *11*(2), 157-173. https://doi.org/10.1108/BEPAM-02-2020-0026

Safapour, E., Kermanshachi, S., & Rouhanizadeh, B. (2022). Key components of successful post–hurricane reconstruction of transportation infrastructures. *Built Environment Project and Asset Management*, *12*(5), pp.775-791. https://doi.org/10.1108/BEPAM-05-2021-0071

Safapour, E., Kermanshachi, S., & Pamidimukkala, A. (2021). Post-disaster recovery in urban and rural communities: Challenges and strategies. *International Journal of Disaster Risk Reduction*, *64*, 102535. https://doi.org/10.1016/j.ijdrr.2021.102535

Safapour, E., Kermanshachi, S., & Rouhanizadeh, B. (2023). Prediction of cost and schedule performance in post-hurricane reconstruction of transportation infrastructure. *PLoS one*, *18*(3), p.e0282231. https://doi.org/10.1371/journal.pone.0282231

Wu, T. (2021). Quantifying coastal flood vulnerability for climate adaptation policy using principal component analysis. *Ecological Indicators*, *129*, 108006.