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The Spatiotemporal Patterns of Community Vulnerability in the U.S. Mobile Bay from 2000–2020

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Abstract

The coastal community is confronted with heightened risks posed by climate change. Mobile Bay in the United States is a large estuarine system along the Gulf of Mexico (GOM) coast, providing critical ecosystem services for the nation. This region is however subject to increased urbanization and uncertain impacts of climate change. To ensure sustainability of this important ecosystem, it is imperative to examine the changing spatial patterns of community vulnerability to environmental changes in this region. Using data from the U.S. Census of multiple years, we investigate the changing spatial patterns of social vulnerability at the census block group level in Mobile Bay consisting of Mobile County and Baldwin County over the past 20 years (2000 – 2020). Additionally, we utilize hotspot and cluster analyses to formalize the observations of the spatiotemporal changes. Further, we examine how land use and land cover (LULC) changes co-occur with social vulnerability changes across Mobile Bay. We identify several hotspots where land cover has been converted to urban land and social vulnerability has increased. The investigation of the spatial patterns over a relatively long period helps to deepen the insight into the dynamic spatiotemporal changes of social and environmental vulnerability. This insight can better inform future plans to cope with climate change and ensure sustainability. Specifically, hotspots that have undergone urbanization and increased social vulnerability demand special attention from policy makers for future risk mitigation and disaster planning.

Keywords Changing spatial patterns · Environmental change · Community vulnerability · GIS

Introduction

The coastal region is confronted with heightened risks posed by climate change (IPCC, 2022). Due to the growing human population in the coast, climate change coupled with human activities would pose a larger threat to the health and

Extended author information available on the last page of the article well-being of coastal communities in coming years (Pan et al., 2021; Shao et al., 2020). The U.S. coastal communities are highly vulnerable to the adverse impacts of climate change and are already experiencing increased impacts of persistent climate stressors such as floods, hurricanes, and sea level rise (Gang et al., 2020). Coastal communities in the United States are projected to suffer great amounts of economic damage due to climate change-induced higher storm surges (Fleming et al., 2018). Under climate change, coastal flooding caused by hurricanes is projected to increase in frequency and intensity (Lin & Emanuel, 2016; Lin et al., 2016). The compound effects of tropical cyclone climatology and sea level rise will exacerbate coastal flooding in the U.S. Gulf of Mexico by the late twenty-first century (Marsooli, et al., 2019). Mobile River Basin (MRB), as one of the most biologically diverse regions of the continental U.S., provides critical ecosystem services to the nearby community and the country. The MRB occupies more than 20 forest ecosystems and ten wetland types. Specifically, the MRB are valuable natural resources to the southeast United States. However, the coastal ecosystem of MRB and its adjacent coasts are vulnerable to environmental stressors induced by local human activities and global climate change. In 2017, the Mobile River was listed as one of the top ten "Most Endangered Rivers in the nation." Human needs for transportation, housing, water supply, food, and timber have changed the basin's habitat's nature and quality, resulting in the fastest biotic extinctions in the continental U.S.

Mobile Bay is a large estuarine system along the Gulf of Mexico (GOM) coast. It is located within the state of Alabama, along the north-central Gulf of Mexico (Fig. 1). An ecologically and economically important region to the nation, Mobile Bay is however under increasing pressure of rapid urbanization and uncertain impacts of climate change (Ellis et al., 2011). Mobile Bay was designated as an estuary of "national significance" in 1996 (MBNEP, 2008). The estuary contributes to economic development in terms of shipping, Gulf of Mexico fisheries, and recreation (MBNEP, 2008). Given its extraordinary aquatic and terrestrial biodiversity, the rapid land use land cover changing patterns are expected to negatively affect the estuary's health (Ellis et al., 2011). Meanwhile, this region is susceptible to storm surges and wind damage from hurricanes. In the last 50 years, several major hurricanes have impacted this region, with Hurricane Frederic (Category 3, 1979) and Hurricane Katrina (Category 4, 2005) being the most destructive ones (Ellis et al., 2011). The largest surge in recent history was recorded during Hurricane Frederick (1979), exceeding four meters (Shao et al., 2019). During Hurricane Katrina, high storm surge of 3.5 m was recorded at the Mobile State Docks (Ellis et al., 2011). A Katrina-like hurricane would cause damages to the Port of Mobile as much as seven times of the damage incurred by Katrina (Abdelhafez et al., 2021). In addition, hurricane wind risk is found to be the highest in the middle of the Gulf coast including the Alabama coastline (Trepanier et al., 2015). It is thus imperative to prepare the coastal community in Mobile Bay for future climate change risks. The first necessary step would be to understand the changing spatiotemporal patterns of community vulnerability in recent history so that the information can guide future resilience plans and help decision makers allocate resources to places with high vulnerability (Folke, 2006).

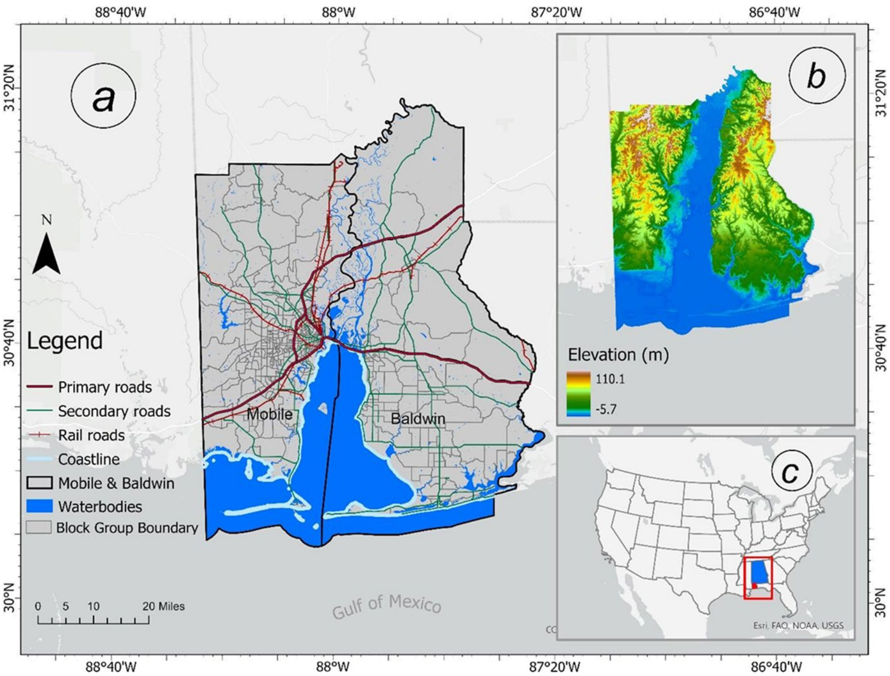

Fig. 1 Study area map (**a**) administrative map of Mobile Bay (**b**) elevation map of Mobile Bay (**c**) location of study area and Alabama State in context of CONUS

Vulnerability is defined as: "The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards" (UNISDR, n.d.). Considering the ecological importance of Mobile Bay and the watershed, it is vital to evaluate the vulnerability of this region due to exposure to hazards or perturbations (Turner et al, 2003). Social and natural systems are increasingly integrated and should be considered for a more holistic approach to vulnerability assessment. Understanding social–ecological system vulnerability requires comprehending both the social vulnerability and ecological vulnerability of the system (Beroya-Eitner, 2016).

Ecological vulnerability is considered a function of three components including susceptibility to exposure, sensitivity to the stressor and system recovery potential, all of whichare influenced by system characteristics (Beroya-Eitner, 2016). Ecological vulnerability assessment of Mobile Bay can provide valuable information regarding hazards as well as their impact on coastal ecosystems or other socioeconomic systems such as population, community, and landscape (Beroya-Eitner, 2016). Hazards can be natural or anthropogenic and may either result in short-term perturbation or long-term disturbances. The risks caused by climate, sea level rise and land use and land cover change in Mobile Bay region could be evaluated according to the ecological vulnerability analysis. In this study, we focus on socioeconomic and environmental characteristics of a community that are predisposed to the negative impacts of environmental stressors. Social vulnerability to environmental hazards refers to the potentiality of loss of life and property damage during any events of natural hazards (Cutter et al., 2003). Assessing, especially quantifying social vulnerability helps policy makers gauge the incapability of a particular community to predict, mitigate, and recover from the impact of any natural hazards (Frigerio et al., 2016). To mitigate the detrimental impacts of hydrological hazards such as floods and hurricanes, and to build a resilient community, the spatial identification of the vulnerable population as well as reaching out to them is crucial (Roder et al., 2017). It will help to alleviate the severity of life loss and property damage during a catastrophe. Social vulnerability index (SoVI) has been widely applied in different geographic regions and at varying scales. Two predominant algorithms have emerged over the past 20 years. The first algorithm considers a wide range of sociodemographic variables that are usually derived from census data, applies Principal Component Analysis (PCA) to condensing the essential information into a fewer number of factors, and aggregates the factors into a composite index (Cutter et al., 2003). This algorithm is found to be sensitive to the change of geographic region and unit of analysis (Schmidtlein et al., 2008). The second algorithm selects a number of socioeconomic variables based on the social vulnerability literature, organizes the variables into four themes, and ranks a geographic unit (e.g., census tract or county) against one another within a state or the entire U.S. for each variable and each theme (Flanagan et al., 2011).

Despite a large number of social vulnerability studies in the existing literature, the present study offers three novelties. First, unlike many previous studies that focused on county (Cutter et al., 2003; Emrich & Cutter, 2011) and census tract (Flanagan et al., 2011) within a large geographic region such as the contiguous U.S. and the Southeast U.S., this study focuses on a finer geographic unit: census block group within a small area Mobile Bay. The spatial distribution of social vulnerability at such a fine scale can assist decision makers more efficiently allocate resources in the event of an emergency. Second, instead of providing a snapshot of the spatial distribution of social vulnerability at one point of time, this study provides a series of maps demonstrating the changing landscape of social vulnerability over the span of two decades. Furthermore, hotspot and cluster analyses are utilized to formalize the observation of the spatiotemporal changes. The investigation of the spatial patterns over a relatively long period of time helps to deepen the insight into the dynamic spatiotemporal changes of social vulnerability. This insight can better inform future plans to cope with climate change. Third, along with social vulnerability, this study examines the changing pattern of land use and land cover (LULC) over the past 20 years. It is significant to examine LULC changing patterns because social vulnerability to environmental stressors could be accelerated by the changing pattern of LULC (Li et al., 2016). For instance, insufficiently planned urbanization, vegetation loss and waterbodies degradation can directly exacerbate social vulnerability. Therefore, it is crucial to detect the LULC changing pattern along with social vulnerability assessment. This pattern can provide insight into the broad environmental changes in this region.

Data and Methods

Study Area

Mobile Bay is an inlet of the Gulf of Mexico, located within the state of Alabama in the United States (Fig. 1). It is surrounded by two counties: Mobile and Baldwin. The mouth of the Mobile Bay was formed by Fort Morgan Peninsula located in Baldwin County in the east and Dauphin Island of Mobile County in the west (Estes et al., 2015). Known for its exceptional aquatic and terrestrial biodiversity, Mobile Bay is ecologically and economically significant as it is the fourth largest estuary in the U.S. (Danielson et al., 2013). The freshwater discharge from the Mobile Bay watershed ranks the fourth among watersheds in the continental U.S. (Lehrter, 2008). The shallow nature of Mobile Bay leads to freshwater discharge influencing the salinity regime, nutrient distribution, and associated biotic processes in the estuary (Pennock et al., 1999). Increases in agricultural activities could potentially exacerbate the current situation. Alarcon and McAnally (2012) estimated that over seventeen years some portions of the Tombigbee watershed underwent substantial increases of agricultural lands and lands used for grazing or hunting animals as well as decrease of natural forest lands. With the significant transformation in soil surface coverage brought by LULC changes, the transport of nutrient and sediments washed-off from this watershed to Mobile Bay and the Alabama Gulf Coast has increased accordingly (Alarcon & McAnally, 2012). To further complicate matters, this region is highly susceptible to many natural disasters associated with climate change such as hurricanes and floods (Ellis et al., 2011). In addition, the elevation of Mobile Bay ranges from 110.1 m to -5.7 m above sea level (Fig. 1b).

Data Sources

A total of ten relevant variables were selected after a meticulous literature review (Aksha et al., 2019; Cutter et al., 2003; Roder et al., 2017; Shao et al., 2020; Wood et al., 2010) combined with the fact that only a limited number of variables are available at the census block group level to assess social vulnerability of the Mobile Bay (Table 1). Selecting these variables was initially an enormous challenge because of the limited variables availability for a administrative unit- block groups level. Despite the unavailability of variables, this study attempted to gather essential variables representing social vulnerability such as population density, economic status, age, gender, education, race and ethnicity. Data for each variable were extracted for three consecutive decennial censuses i.e. 2000, 2010 and 2020 American Community Survey (ACS) five-year estimation from US Census Bureau (https://data.census.gov/cedsci) at block group level. Some of the variables for the 2010 census were extracted from 2013 ACS five-years estimation as it is the most approximated. Next, each variable was normalized before PCA was conducted to reduce data dimensions. Meanwhile, LULC data for 2001, 2011 and 2019 of Mobile Bay region were collected from the National Land Cover Database (NLCD).

Table 1 Description of data variables considered to assess social vulnerability

Variable name	No	Variable description
Z_PopDen	1	Population density (person/sqkm)
Z_HousingDen	2	Housing unit density (house/sqkm)
Z_Income	3	Median households' income (Dollars)
Z_WhitePop	4	Percentage of white alone households
Z_BlackPop	5	Percentage of black alone households
Z_NoVehicle	6	Households with no available vehicle
Z_FemalePop	7	Percentage of total female population
Z_Under5	8	Percentage of population under 5 years old
Z_Above65	9	Percentage of population above 65 years old
Z_NoSchoolC	10	Percentage of population with no schooling completed

Methodology

Social Vulnerability Index (SoVI) Assessment

In this study, the algorithm developed by Cutter et al. (2003) to construct the Social Vulnerability Index (SoVI) was adopted to assess the social vulnerability of Mobile Bay from 2000—2020. Principal component analysis (PCA) (Abson et al., 2012), a data dimension reduction technique, was applied to generate each component of the SoVI (Fig. 2). To construct SoVI, ten crucial social vulnerability variables either in percentage or density were extracted initially from the Census ACS data and normalized based on their characteristics. Kaiser–Meyer–Olkin (KMO) test was also conducted to check adequacy of the sample and multicollinearity in the data. Following that, all the variables were standardized using Z-score equation (Eq. 1),

$$Z = \frac{(x - \mu)}{\sigma} \tag{1}$$

where, Z is standardized value, x is the value of each variable, μ is the mean value of each variable, σ in the standard deviation of each variable.

After calculating Z values for all the variables, PCA was conducted using SPSS software. In this case, varimax rotation (100 iterations) was considered to extract factor components from the census data. Following that, factor components were selected based on their eigenvalue (eigenvalue must be greater than 1.00). Guided by this criterion, there are three factor components found for census data 2000 and four factor components found for census data 2010 and 2020 (Table 2). These factors were named after their dominant variables according to the factor loading. Only variables which have factor loading values greater than 0.650 or less than -0.650 were taken into consideration for naming. Next, cardinality of each factor was assigned based on their individual influences on social vulnerability. For instance, population and housing density have high factor loading (0.864 and 0.861 respectively) in the F1 factor of 2000 data. Since population and housing density positively influences social vulnerability, cardinality was assigned positive (+) for this F1 factor.

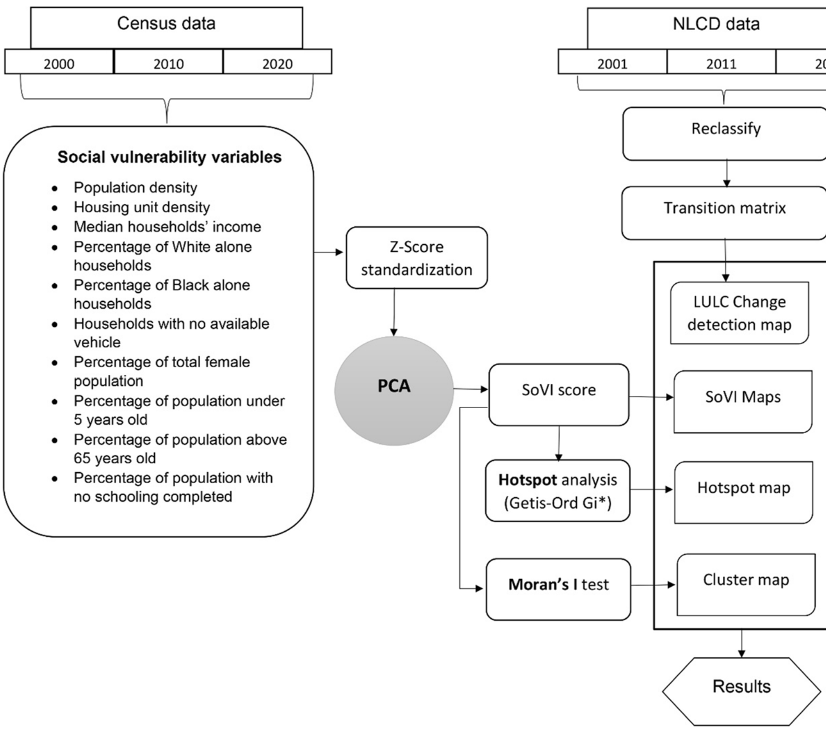

Fig. 2 Methodological flowchart of this study

In order to create a composite SoVI, the weight of each factor needed to be assessed. In the literature, there is no consensus on how to weigh each factor given there is a lack of theoretical arguments supporting particular weighing schemes. A vast number of studies assign equal weight to each factor (Rufat et al., 2015). However, such assumption can be problematic as the social vulnerability outcome is sensitive to different weighting schemes (e.g., weighted vs. non-weighted) (Reckien, 2018). Some studies use the percentage of variance explained to weight each selected constituent factor (Chen et al., 2021; de Sherbinin & Bardy, 2015). One of the primary objectives to map social vulnerability is to guide policy makers in allocating resources to places/areas where they are needed the most. Spatial variations can illustrate the disparities of variables/factors across space. Using ratios of variance explained to the total variance explained by the selected factors to represent contributions to the final social vulnerability outcome can highlight factors that display the most variances explained in a spatial context which consequently highlights areas that need the most attention from policy makers. Thus, this study used the proportion of variance explained by each selected factor as the weight. Specifically, weights of these factors were assessed by calculating the ratio of the variance explained by each factor to the total variance explained by all selected factors. To generate the SoVI, all the factors were summed up by multiplying individual weights

Table 2 Social vulnerability component summary

Census year	Factor	Cardinality	Name	% Variance explained	Dominant variables	Factor loading
2000	F1	+	Population & Housing	43.11	Z_PopDen	0.864
					Z_HousingDen	0.861
	F2	+	Wealth, Race & education	15.03	Z_Income	−0.745
					Z_WhitePop	−0.731
					Z_BlackPop	0.705
					Z_NoSchoolC	0.795
	F3	+	Age	10.7	Z_Under5	−0.814
					Z_Above65	0.826
2010	F1	+	Wealth & Race	33.88	Z_Income	−0.842
					Z_WhitePop	−0.697
					Z_BlackPop	0.713
	F2	+	Population & Housing	13.36	Z_PopDen	0.931
					Z_HousingDen	0.936
	F3	+	Age	12.58	Z_Above65	0.840
	F4	+	Gender (Female)	10.22	Z_FemalePop	0.902
2020	F1	+	Wealth & Race	31.79	Z_Income	−0.782
					Z_WhitePop	−0.780
					Z_BlackPop	0.827
	F2	+	Population & Housing	14.73	Z_PopDen	0.891
					Z_HousingDen	0.883
	F3	+	Age	12.61	Z_Under5	−0.813
					Z_Above65	0.767
	F4	+	Gender (Female)	10.75	Z_FemalePop	0.840

with each factor. Equation 2, 3 and 4 represent SoVI equations for 2000, 2010 and 2020 census data respectively.

$$\mathrm{SoVI}_{2000} = 0.62\ \mathrm{F1} + 0.22\ \mathrm{F2} + 0.16\ \mathrm{F3} \tag{2}$$

$$\mathrm{SoVI}_{2010} = 0.48\ \mathrm{F1} + 0.19\ \mathrm{F2} + 0.18\ \mathrm{F3} + 0.15\ \mathrm{F4} \tag{3}$$

$$\mathrm{SoVI}_{2020} = 0.45\ \mathrm{F1} + 0.21\ \mathrm{F2} + 0.18\ \mathrm{F3} + 0.16\ \mathrm{F4} \tag{4}$$

Following that, SoVI scores were joined with the block group shapefile of Mobile Bay and classified into five major categories (very low, low, moderate, high and very high) using the quantile classification method in ArcGIS Pro software.

Social Vulnerability Hotspot Analysis

In this study, the Hotspot analysis tool (Getis-Ord Gi*) from ArcGIS Pro toolbox was applied to the SoVI to visualize the socially vulnerable hotspot zones in the Mobile Bay. In this case, polygon contiguity conceptualization was adopted for this hotspot analysis to define spatial relationship among block groups. Positive Gi* value represents hotspot zone and negative Gi* value represents the cold spot zone of social vulnerability.

Social Vulnerability Cluster Analysis

To investigate the changing pattern of the social vulnerability clusters, spatial autocorrelation tests including Global Moran's I and Local Moran's I test developed by Anselin (1995) were used in this study. These tests were applied to the SoVI scores of each decade. The value of Global Moran's I ranges between + 1 to -1. Moran's index values close to + 1 indicate high spatial autocorrelations or high level of cluster, values close to -1 suggest low spatial autocorrelation or low level of cluster and value of 0 indicates random spatial patterns without significant autocorrelations (Frigerio et al., 2018). In addition, Local Moran's I test, Cluster and Outlier analysis (Anselin Local Moran's I) were applied to illustrate the spatial distribution of social vulnerability clusters throughout the Mobile Bay region. In this study, polygon contiguity conceptualization was used to define spatial relationships among block groups. The entire region was categorized into five major groups in terms of social vulnerable clusters. These are, High-High cluster (high vulnerable block groups surrounded by other high vulnerable block groups); High-Low outlier (high vulnerable block groups surrounded by low vulnerable block groups); Low–High outlier (low vulnerable block groups surrounded by high vulnerable block groups); Low-Low cluster (low vulnerable block groups surrounded by low vulnerable block groups) and not significant cluster.

LULC Change Detection

Land cover data collected from NLCD website was reclassified into six major types including waterbodies, urban and built-up land, barren land, forestland, grass and agricultural land, and wetland. Next, the transition matrix was generated using ArcGIS Pro software. Transition matrix is a matrix that helps to quantify the transformation of one particular LULC class to another LULC class (Twisa & Buchroithner, 2019). Each cell of the transition matrix demonstrates the actual conversion among LULC classes from one to another while the diagonal cells represent the unchanged land classes throughout the study period (Areendran et al., 2013). So, in this study, a transition matrix was created to investigate land cover changing patterns of Mobile Bay from 2001 to 2019. Using the information from the transition matrix, a Sankey diagram was also produced using Python language to visualize the LULC transition more clearly. Following that, a bar chart was produced to visualize the land cover changes for each major type.

Analysis on the Link Between LULC and Social Vulnerability Changes

To examine the link between LULC changes and social vulnerability changes, raster files of LULC from two different periods (2001 and 2019) were converted into polygon features using the raster to polygon tool available in ArcGIS Pro. The dissolve tool was then used to keep each LULC class in one polygon. After that, the intersect tool was used to detect actual transitions among different LULC types. This analysis focused solely on investigating the conversion of different LULC types into urban land. Meanwhile, social vulnerability changes from 2000 and 2020 were analyzed using a similar approach. Among five classes of social vulnerability, very low and low classes have been reclassified as low and very high and high reclassified as high. The intersect tool was then adopted to detect the changes of social vulnerability among low, moderate, and high levels. Afterwards, the map depicting changes from various LULC types to urban land was overlaid with the map showing changes in social vulnerability.

Results and Discussion

Spatio-temporal Analysis of Social Vulnerability Change

This study found that the social vulnerability has increased vastly in the past 20 years in the Mobile Bay region. Figure 3 illustrates the steady increase of social vulnerability over time, especially in the center and surrounding area of Mobile city. Meanwhile, some cities in the northern part of Mobile County namely Prichard, Chickasaw, Saraland, Satsuma and Creola city had experienced the gradual surge of social vulnerability in the past two decades. The periphery of Mobile City had low social vulnerability in 2000. These areas became highly socially vulnerable by 2010 and further increased in size by 2020. In addition to that, the northern part of Mobile County had experienced a dramatic increase in social vulnerability from 2010 to 2020.

On the other hand, vast social vulnerability changes were also noticed in Baldwin County. The northern part of Baldwin County experienced a strong surge of social vulnerability. In addition, the coastal cities of Baldwin County such as Gulf shores and Orange Beach rose steadily from low to high vulnerability over time, mainly due to population growth. Moreover, Foley, Daphne and Fairhope cities inside Baldwin County experienced slight increase of social vulnerability in the last two decades.

Overall, in 2000, 135 block groups out of 336 were identified having either very high or high vulnerability social vulnerability in Mobile County and Baldwin County, respectively. In 2010, among 363 block groups in Mobile Bay, 143 block groups were found to have either very high or high social vulnerability in the study area, respectively. However social vulnerability expanded substantially in 2020, among all 452 block groups, there were 181 block groups that were identified as either very high or high social vulnerable in Mobile County and Baldwin County, respectively.

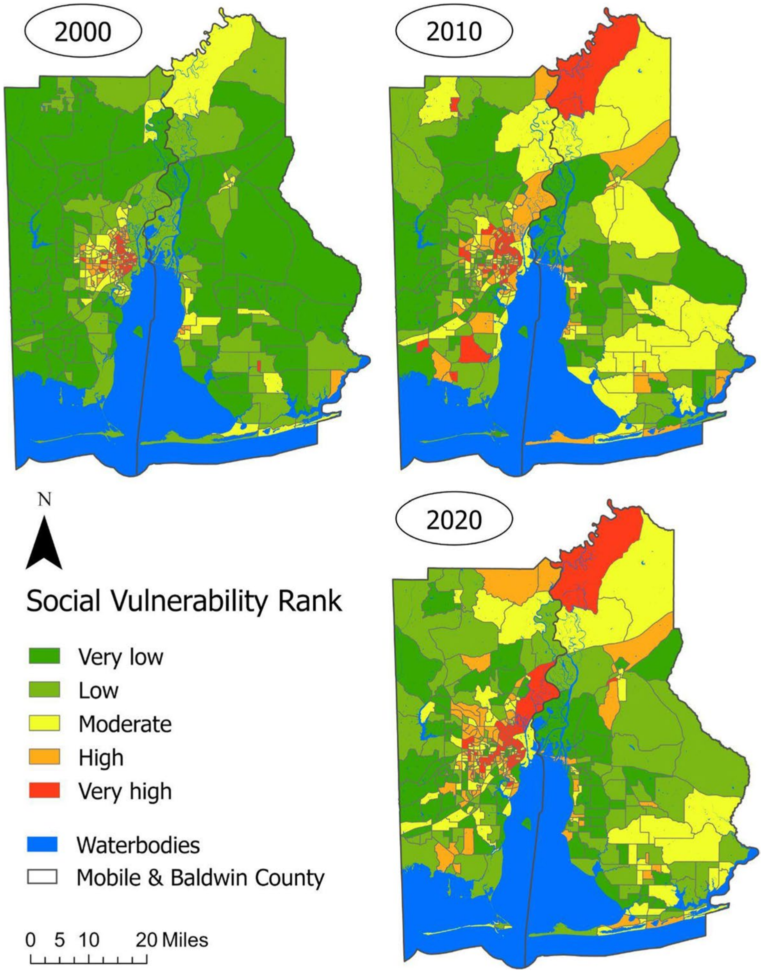

Fig. 3 Spatial distribution of social vulnerability in Mobile Bay

Hotspots and Cluster Analysis

To formalize the observations made by observing the maps, hotspot and cluster analysis were utilized. Substantial expansion of hotspot area and reduction of cold spot area over time are obvious in these maps (see Fig. 4). Hotspot maps clearly depict that the socially vulnerable hotspots are centered in Mobile city and its surrounding area. Hotspot expansion can be clearly detected in the surrounding area of Mobile city. On the other hand, a large cold spot area was detected in coastal Baldwin County in 2000. However, it became a non-significant zone in 2010 and 2020. Figure 4 also shows that the coastal area of Baldwin County has fallen into a non-significant zone since 2000.

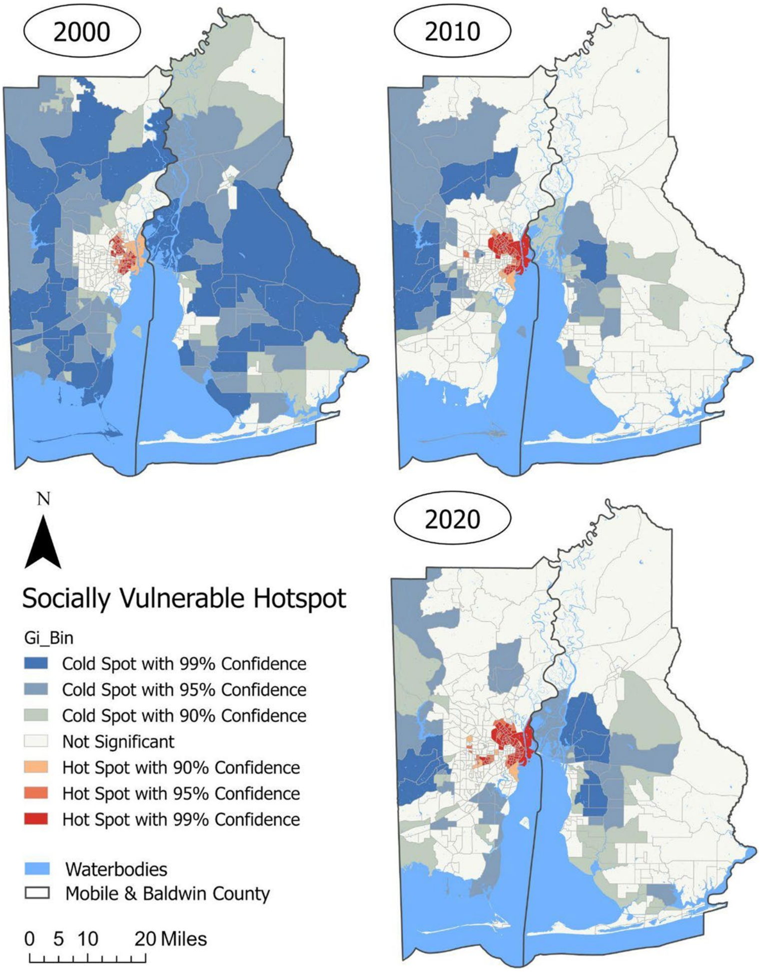

Fig. 4 Socially vulnerable hotspot in Mobile Bay

The Global Moran's I results indicate a positive spatial autocorrelation for all decades. In the years of 2000, 2010 and 2020, Moran's indexes were 0.62, 0.54 and 0.54, respectively, while z values were 18.46, 16.82 and 18.79. These values indicate highly clustered spatial patterns among social vulnerability clusters.

From Local Moran's I cluster analysis, High-High cluster was detected in the middle of Mobile city (Fig. 5). Further, High-High social vulnerability clusters have expanded vastly in the western part of the city in the last two decades. Meanwhile, Low–High social vulnerability clusters detected alongside the Mobile Bay coast in Mobile City. Except for a few regions, almost the entire study area was Low-Low cluster in 2000, which converted into different clusters over time. However, most of the coastal part of Baldwin County was a Low-Low cluster in 2000 which converted into a non-significant cluster in 2010 and 2020.

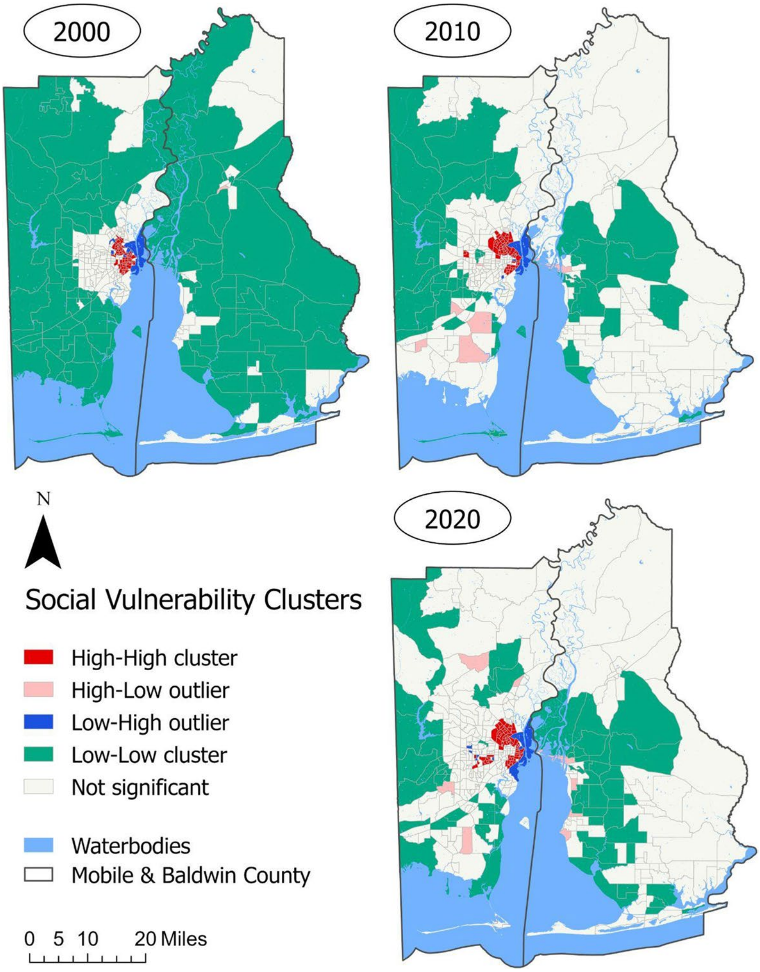

Fig. 5 Spatial distribution of social vulnerability clusters in Mobile Bay

Spatiotemporal Analysis of LULC Change in Mobile Bay

According to the spatiotemporal LULC change analysis, the land cover of Mobile Bay has changed substantially over the past two decades. The dynamic transition of the land cover over the period are shown in the Sankey diagram (Fig. 6). Noticeably, urban and built up areas increased dramatically from 2001 to 2019, growing from 85,747.05 hectare (8.96%) in 2001 to 97,488.32 hectare (10.18%) in 2019. This Sankey diagram shows that 394.57 hectare (0.4%) of barren land, 5409.76 hectare (5.55%) of forest land, 5781.46 hectare (5.93%) of grassland, 193.27 hectare (0.2%) of permanent water bodies, and 1062.81 hectare (1.09%) of wetlands were converted into urban and built-up area over the period. More detailed information about the

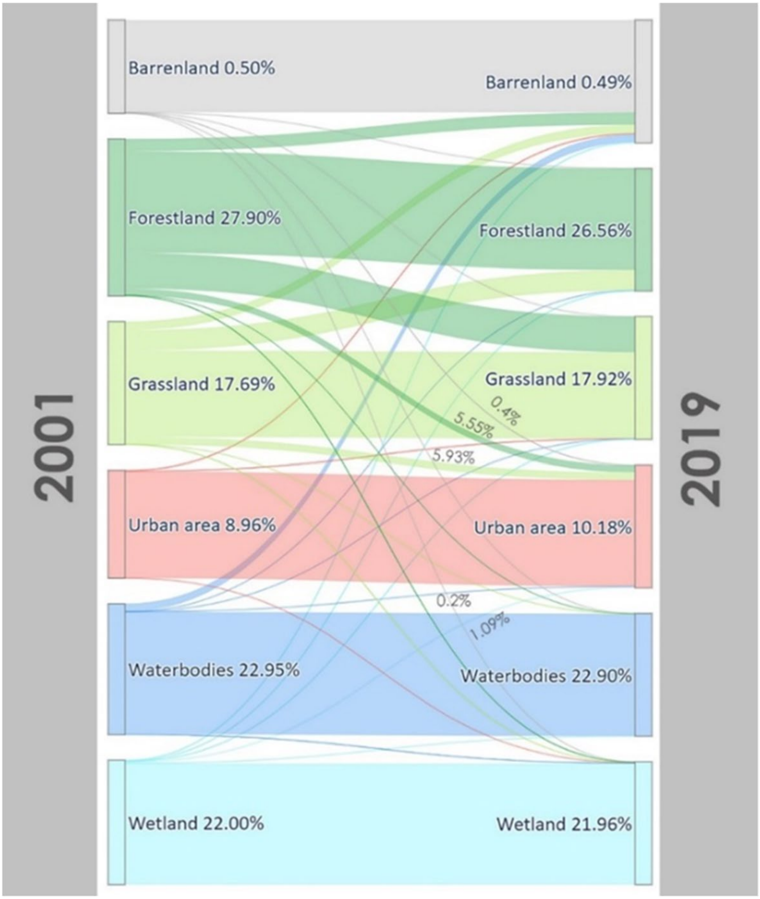

Fig. 6 Sankey diagram of LULC changes in Mobile Bay from 2001 to 2019

LULC changes can be found in Supplementary Material Figure 1 maps of LULC types of Mobile Bay and Supplementary Material Table 1 of transition matrix.

The expansion of urban and built-up areas in Mobile City over the two decades is clearly demonstrated in Fig. 7. A few places in Baldwin County (Spanish fort, Daphne and Fairhope) have also experienced dramatic expansion of the urban area. Moreover, urban and built-up areas in the coastal part of Baldwin County, such as the Gulf Shore and its northern region, have increased to a large degree in the past two decades.

The bar chart clearly shows the increase of urban area during the study period (2001–2019) in the entire Mobile Bay region (Fig. 8). In 2001, urban area was 8.96% of the total area, which increased to 9.89% in 2011 and it enlarged to 10.18% in 2019. A small change can be noticed in forest and grassland but

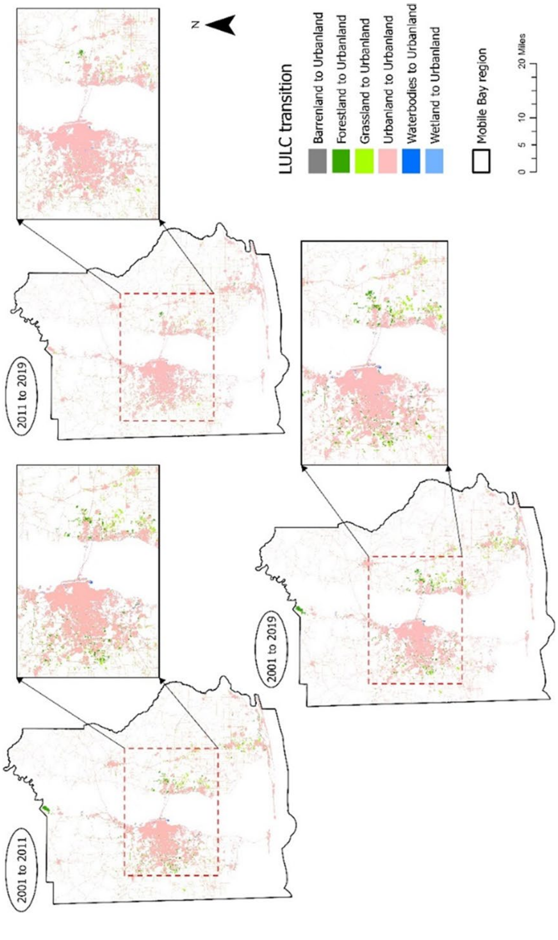

Fig. 7 Temporal analysis of LULC change dynamics in Mobile Bay

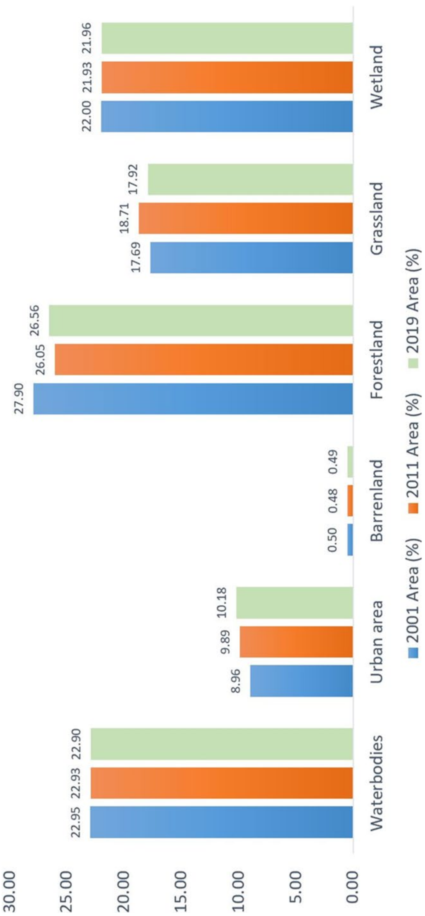

Fig. 8 Bar chart of LULC change for the years of 2001, 2011 and 2019

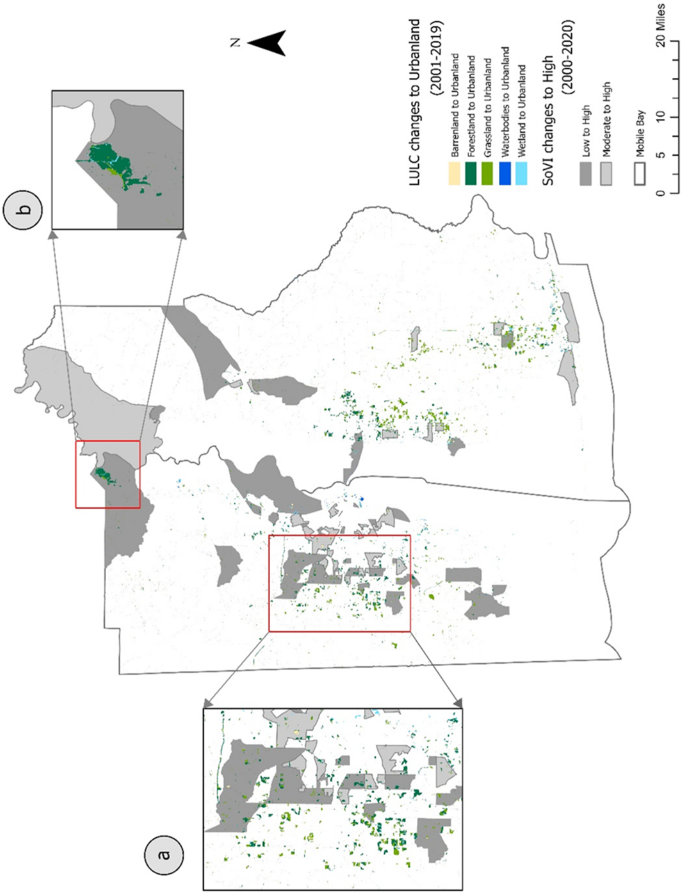

Fig. 9 The link between LULC changes and social vulnerability changes

permanent water bodies, wetland and barren land remain stable throughout the two decades.

The Link Between LULC Changes and Social Vulnerability Changes

The link between LULC changes and social vulnerability changes has been demonstrated in Fig. 9. Based on the analysis conducted, the region surrounding the conversion of forestland and grassland into urban land has experienced a significant change in social vulnerability, transitioning from low to high (Fig. 9).

Similarly, in Fig. 9b, a vast area was converted to urban land from forestland. Consequently, social vulnerability of that region was shifted from low to high for the past 20 year. This co-occurrence of LULC shift to urban land and elevated social vulnerability over time suggests that urbanization accompanied by population concentration can increase coastal community's exposure to hazards and disasters. Special attention from policy makers needs to be paid to these particular areas and risk mitigation action plans need to be put in place.

Conclusion

Mobile Bay and its surrounding area are highly susceptible to a number of natural hazards such as floods and hurricanes, which are compounded by sea level rise under climate change. In order to effectively mitigate the devastating impact of these coastal hazards on the human community, it is critical to spatially identify socially vulnerable regions so that resources can be allocated more efficiently for disaster planning, response, and recovery. This study made an attempt to assess social vulnerability in the Mobile Bay area for two consecutive decades (from 2000—2020). A series of maps were constructed to display the changes of spatial distribution of social vulnerability over the study period. Further, hotspot analysis and cluster analysis were utilized to formalize the observations made by examining the maps of social vulnerability in 2000, 2010, and 2020, respectively. Overall, the area with high social vulnerability has vastly enlarged inside Mobile County, and also expanded in the northern part of Baldwin County. Along with social vulnerability, LULC changes were examined and detected. According to LULC change detection analysis, the urban and built-up area expanded to a large extent (11,741.27 hectares) from 2001 to 2019. Corresponding to urban expansion, the center of Mobile City has experienced an increasing trend of social vulnerability throughout the two decades. Socially vulnerable hotspot zones have been expanding toward the northwestern part of Mobile City in the last two decades. Therefore, it can be concluded that the community inside the Mobile City is becoming increasingly susceptible and vulnerable to coastal hazards, as a result of population growth and urban expansion over time.

Understanding the spatiotemporal dynamics of social vulnerability changes as well as LULC shift to urban land is vital for adopting effective disaster risk reduction strategies. Such understanding can effectively help with efficient allocation of our limited resources during all phases of disaster management cycle (long-term risk mitigation, preparedness, response, and recovery), resulting in the reduction of post disaster human suffering and economic losses (Flanagan et al. 2011). Results of this study are believed to assist policymakers in an effective disaster risk reduction process by highlighting socially vulnerable hotspot areas of Mobile Bay and providing a better understanding about spatiotemporal patterns of social vulnerability changes. This understanding will support disaster management authority of Mobile Bay in risk mitigation and preparedness planning by providing insights of optimal locations of the future disaster resilient infrastructure, e.g., shelter centers, disaster recovery centers and pre-disaster training centers, all of which should be located in or close to highly vulnerable areas. Moreover, findings of this study will assist with the development of emergency response and recovery strategies during and post disasters by prioritizing highly vulnerable regions when allocating limited resources such as rescue equipment and effort, relief and recovery resources. Furthermore, the correlation analysis highlighting the relationship between the dynamic pattern of LULC changes and the corresponding changes in social vulnerability would generate interest in further research on LULC changes and their relationship with social vulnerability change. Overall, this study can help the authority and policymakers make strategic plans to reduce social vulnerability in Mobile Bay and to develop a strong coping capacity during natural hazards.

There are several limitations in this study. First, because of the choice of census block group, many variables that are available at the county and census tract level are no longer available. As a result, a smaller number of variables are selected to construct SoVI. Second, there is no consensus on how to weigh each component of the SoVI in the literature. The proportion of variance explained by each factor is used as the weighting scheme. Some researchers use experts' input to weigh each factor. For instance, the analytic hierarchy process (AHP) has been widely used to estimate relative weights of factors in the complex decision-making context (Forman & Gass, 2001). Future studies on SoVI can consider this approach. Third, although the changing spatial patterns of social vulnerability are identified over two decades, this study has yet to validate the results, similar to most studies on SoVI. Moving forward, this line of research needs to create a framework to validate SoVI. Validation can be built upon the comparison of different weighting schemes.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdelhafez, M. A., Ellingwood, B., & Mahmoud, H. (2021). Vulnerability of seaports to hurricanes and sea level rise in a changing climate: A case study for mobile, AL. *Coastal Engineering, 167*, 103884. https://doi.org/10.1016/j.coastaleng.2021.103884

Abson, D. J., Dougill, A. J., & Stringer, L. C. (2012). Using principal component analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. *Applied Geography, 35*(1–2), 515–524. https://doi.org/10.1016/j.apgeog.2012.08.004

Aksha, S. K., Juran, L., Resler, L. M., & Zhang, Y. (2019). An analysis of social vulnerability to natural hazards in Nepal using a modified social vulnerability index. *International Journal of Disaster Risk Science, 10*(1), 103–116. https://doi.org/10.1007/s13753-018-0192-7

Alarcon, V. J., & McAnally, W. H. (2012). A strategy for estimating nutrient concentrations using remote sensing datasets and hydrological modelling. *International Journal of Agricultural and Environmental Information Systems*, *3*(1). https://doi.org/10.4018/jaeis.2012010101

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis, 27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Areendran, G., Rao, P., Raj, K., Mazumdar, S., & Puri, K. (2013). Land use/land cover change dynamics analysis in mining areas of Singrauli district in Madhya Pradesh, India. *Tropical Ecology, 54*(2), 239–250. https://doi.org/10.1016/j.ejrs.2018.01.002

Beroya-Eitner, M. A. (2016). Ecological vulnerability indicators. *Ecological Indicators, 60*, 329–334. https://doi.org/10.1016/j.ecolind.2015.07.001

Chen, Y., Ye, Z., Chen, R., & Liu, Z. (2021). A GIS-based approach for flood risk zoning by combining social vulnerability and flood susceptibility: A case study of Nanjing, China. *International Journal of Environmental Research and Public Health, 18*(21), 11597.

Cutter, S., Boruff, B., & Shirley, W. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly, 84*(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

Danielson, J. J., Brock, J. C., Howard, D. M., Gesch, D. B., Bonisteel-Cormier, J. M., & Travers, L. J. (2013). Topobathymetric model of Mobile Bay, Alabama. *US Geological Survey Data Series*, *769*(6). https://doi.org/10.3133/ds769

de Sherbinin, A., & Bardy, G. (2015). Social vulnerability to floods in two coastal megacities: New York City and Mumbai. *Vienna yearbook of population research*, 131–165.

Ellis, J. T., Spruce, J. P., Swann, R. A., Smoot, J. C., & Hilbert, K. W. (2011). An assessment of coastal land-use and land-cover change from 1974–2008 in the vicinity of Mobile Bay, Alabama. *Journal of Coastal Conservation, 15*(1), 139–149. https://doi.org/10.1007/s11852-010-0127-y

Emrich, C. T., & Cutter, S. L. (2011). Social vulnerability to climate sensitive hazards in the southern United State. *Weather, Climate, and Society., 3*(3), 193–208. https://doi.org/10.1175/2011WCAS1092.1

Estes Jr, M. G., Al-Hamdan, M. Z., Ellis, J. T., Judd, C., Woodruff, D., Thom, R. M., ..., & Herder, T. (2015). A modeling system to assess land cover land use change effects on SAV habitat in the Mobile Bay estuary. *JAWRA Journal of the American Water Resources Association*, *51*(2), 513–536. https://doi.org/10.1111/jawr.12263

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management, 8*(1), 3. https://doi.org/10.2202/1547-7355.1792

Fleming, E., Payne, J., Sweet, W., Craghan, M., Haines, J., Hart, J. F., Stiller, H., & Sutton-Grier, A. (2018). Coastal effects. In D. R. Reidmiller, C. W. Avery, D. R. Easterling, K. E. Kunkel, K. L. M. Lewis, T. K. Maycock, & B. C. Stewart (Eds.), *Impacts, risks, and adaptation in the United States: Fourth National Climate Assessment, Volume II* (pp. 322–352). U.S. Global Change Research Program. https://doi.org/10.7930/NCA4.2018.CH8

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change, 16*(3), 253–267. https://doi.org/10.1016/j.gloenvcha.2006.04.002

Forman, E. H., & Gass, S. I. (2001). The analytic hierarchy process—an exposition. *Operations Research, 49*(4), 469–486. https://doi.org/10.1287/opre.49.4.469.11231

Frigerio, I., Carnelli, F., Cabinio, M., & De Amicis, M. (2018). Spatiotemporal pattern of social vulnerability in Italy. *International Journal of Disaster Risk Science, 9*, 249–262. https://doi.org/10.1007/s13753-018-0168-7

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. https://doi.org/10.1016/j.apgeog.2016.06.014

Gang, C., Pan, S., Tian, H., Wang, Z., Xu, R., Bian, Z., Pan, N., Yao, Y., & Shi, H. (2020). Satellite observations of forest resilience to hurricanes along the northern Gulf of Mexico. *Forest Ecology and Management, 472*, 118243. https://doi.org/10.1016/j.foreco.2020.118243

IPCC. (2022). Summary for Policymakers [H.-O. Pörtner, D. C. Roberts, E. S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.), *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 3–33). Cambridge University Press. https://doi.org/10.1017/9781009325844.001

Lehrter, J. C. (2008). Regulation of eutrophication susceptibility in oligohaline regions of a northern Gulf of Mexico estuary, Mobile Bay, Alabama. *Marine Pollution Bulletin, 56*(8), 1446–1460.

Li, Y., Zhang, X., Zhao, X., Ma, S., Cao, H., & Cao, J. (2016). Assessing spatial vulnerability from rapid urbanization to inform coastal urban regional planning. *Ocean & Coastal Management, 123*, 53–65. https://doi.org/10.1016/j.ocecoaman.2016.01.010

Lin, N., & Emanuel, K. (2016). Grey swan tropical cyclones. *Nature Climate Change, 6*(1), 106–111. https://doi.org/10.1038/nclimate2777

Lin, N., Kopp, R. E., Horton, B. P., & Donnelly, J. P. (2016). Hurricane Sandy's flood frequency increasing from year 1800 to 2100. *Proceedings of the National Academy of Sciences, 113*(43), 12071–12075. https://doi.org/10.1073/pnas.1604386113

Marsooli, R., Lin, N., Emanuel, K., & Feng, K. (2019). Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nature Communication., 10*, 3785. https://doi.org/10.1038/s41467-019-11755-z

Mobile Bay National Estuary Program (MBNEP). (2008). State of Mobile Bay. https://www.mobilebaynep.com/assets/pdf/State-of-Mobile-Bay-Final.pdf. Accessed on June 1, 2023.

Pan, S., Bian, Z., Tian, H., Yao, Y., Najjar, R. G., Friedrichs, M. A., Hofmann, E. E., Xu, R., & Zhang, B. (2021). Impacts of multiple environmental changes on long-term nitrogen loading from the Chesapeake Bay watershed. *Journal of Geophysical Research: Biogeosciences, 126*(5), e2020JG005826. https://doi.org/10.1029/2020JG005826

Pennock, J. R., Boyer, J. N., Herrera-Silveira, J. A., Iverson, R. L., Whitledge, T., Mortazavi, B., et al. (1999). Nutrient behavior and phytoplankton production in Gulf of Mexico estuaries. Biogeochem. Gulf of Mexico Estuaries, pp. 109–162

Reckien, D. (2018). What is in an index? Construction method, data metric, and weighting scheme determine the outcome of composite social vulnerability indices in New York City. *Regional Environmental Change, 18*, 1439–1451. https://doi.org/10.1007/s10113-017-1273-7

Roder, G., Sofia, G., Wu, Z., & Tarolli, P. (2017). Assessment of social vulnerability to floods in the floodplain of northern Italy. *Weather, Climate, and Society, 9*(4), 717–737. https://doi.org/10.1175/WCAS-D-16-0090.1

Rufat, S., Tate, E., Burton, C. G., & Maroof, A. S. (2015). Social vulnerability to floods: Review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction, 14*, 470–486. https://doi.org/10.1016/j.ijdrr.2015.09.013

Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W., & Cutter, S. L. (2008). A sensitivity analysis of the social vulnerability index. *Risk Analysis: An International Journal, 28*(4), 1099–1114. https://doi.org/10.1111/j.1539-6924.2008.01072.x

Shao, W., Jackson, N. P., Ha, H., & Winemiller, T. (2020). Assessing community vulnerability to floods and hurricanes along the Gulf Coast of the United States. *Disasters, 44*(3), 518–547. https://doi.org/10.1111/disa.12383

Shao, W., Keim, B. D., Xian, S., & O'Connor, R. (2019). Flood hazards and perceptions – A comparative study of two cities in Alabama. *Journal of Hydrology, 569*, 546–555. https://doi.org/10.1016/j.jhydrol.2018.11.070

Trepanier, J. C., Ellis, K. N., & Tucker, C. S. (2015). Hurricane risk variability along the gulf of Mexico coastline. *PLoS ONE, 10*(3), e0118196. https://doi.org/10.1371/journal.pone.0118196

Turner, B. L., Kasperson, R. E., Matson, P. A., et al. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences, 100*(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100

Twisa, S., & Buchroithner, M. F. (2019). Land-use and land-cover (LULC) change detection in Wami River Basin, Tanzania. *Land, 8*(9), 136. https://doi.org/10.3390/land8090136

Wood, N. J., Burton, C. G., & Cutter, S. L. (2010). Community variations in social vulnerability to Cascadia-related tsunamis in the US Pacific Northwest. *Natural Hazards, 52*(2), 369–389. https://doi.org/10.1007/s11069-009-9376-1

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