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2017 Coastal Master Plan

Attachment C4-11.2: Social Vulnerability Index

Report: Final

Date: April 2017

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Coastal Protection and Restoration Authority

This document was prepared in support of the 2017 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties and responsibilities of CPRA and charged the new authority to develop and implement a comprehensive coastal protection plan, consisting of a master plan (revised every five years) and annual plans. CPRA's mandate is to develop, implement and enforce a comprehensive coastal protection and restoration master plan.

Suggested Citation:

Hemmerling, S.A., and Hijuelos, A.C. (2017). *2017 Coastal Master Plan: Attachment C4-11.2: Social Vulnerability Index.* Version Final. (pp. 1-28). Baton Rouge, Louisiana: Coastal Protection and Restoration Authority.

Acknowledgements

This document was developed in support of the 2017 Coastal Master Plan. The development of the ideas presented here was guided by a larger team that included:

- Coastal Protection and Restoration Authority (CPRA) of Louisiana - Mandy Green, Melanie Saucier, and Karim Belhadjali

The following people assisted with reviewing and formatting this report:

- The Water Institute of the Gulf – Tim Carruthers, Denise Reed, Chincie Mouton and Phillip LaFargue

This effort was funded by the Coastal Protection and Restoration Authority (CPRA) of Louisiana under Cooperative Endeavor Agreement Number 2503-12-58, Task Order No. 38.

Executive Summary

The 2017 Coastal Master Plan utilizes an array of modeling tools to evaluate the effectiveness of restoration and protection projects on the landscape, ecosystems, and communities. The social vulnerability metric, described herein, is a static geographic layer that does not vary through time nor is it linked directly to the master plan modeling tools. Instead the social vulnerability metric can be used to interpret the results of other metrics and master plan model outputs, specifically in terms of their predicted impact on socially vulnerable communities. This report describes the development of the metric and the social vulnerability index values across the coast. Principal components analysis was used to statistically combine a suite of highly correlated socioeconomic variables obtained from the 2010 Census and the 2009-2013 American Community Survey into a number of uncorrelated variables, or principal components, that account for as much of the variability in the data as possible. Weighted values for each of the principal components were then derived and summed to develop a social vulnerability index value for all populated census block groups within the study area. The social vulnerability index calculated for coastal Louisiana offers valuable insights into the social and economic conditions that increase community vulnerability to hazards events. This index enables an assessment of the relative vulnerability of communities and can be used to further interpret the findings of other master plan metrics by comparing metric results across the vulnerability categories determined in this report. Providing community level information to the Planning Tool could further support evaluation of how communities with different levels of vulnerability may be affected by projects or alternatives.

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List of Abbreviations

ACS	American Community Survey
CPRA	Coastal Protection and Restoration Authority
PCA	Principal Components Analysis
SVI	Social Vulnerability Index

1.0 Background

The 2017 Coastal Master Plan utilizes an array of modeling tools to evaluate the effectiveness of restoration and protection projects on the landscape, ecosystems, and communities. The model outputs are used both individually and in combination to create indices, called metrics (see Appendix C, Attachment C4-11), to inform how projects meet the master plan objectives. Metrics can be used to rank projects, formulate alternatives, compare alternatives, and improve understanding of the effects of the plan and its included projects on the coast. None of the existing metrics represent social vulnerability across the coast. The social vulnerability index (SVI), described herein, is a static geographic layer that does not vary through time nor is it linked directly to the master plan modeling tools. Instead, the index can be used to interpret the results of other metrics and master plan model outputs by identifying their predicted impact on communities that are currently socially vulnerable. This report describes the development of the index and results, in terms of SVI values across the coast.

2.0 Introduction

Social impacts of hazard exposure often fall disproportionately on society's most vulnerable populations, including those with low income, minorities, children, the elderly, and the disabled. In broad terms, social vulnerability refers to the inherent characteristics of a person or group that influences their capacity to anticipate, cope with, resist, or recover from the impact of a hazard (Wisner et al., 2004). Inherent social vulnerability can lead to adverse or positive responses to hazards events and is influenced by the following characteristics (Jepson & Colburn, 2013):

- Pre-event socioeconomic structures of the community that may create or negate the potential for harm;
- Susceptibility to harm, powerlessness, and marginality of physical, natural and social systems; and
- Patterns of differential access to resources.

The most widely accepted demographic and social characteristics of residents that make some communities more vulnerable than others are age, gender, race, socioeconomic status, and special needs populations, including the disabled. Additionally, communities that rely on a single economic sector for their livelihoods are more vulnerable than those communities with a diversified economic base (Cutter, 2008). This is especially true of communities that rely economically on natural resources, such as fisheries, for their livelihoods (Jepson & Colburn, 2013; Tuler et al., 2008). One method for identifying the locations of these populations is the SVI approach, a statistical modeling approach that utilizes indicator variables to quantify relative levels of social vulnerability across space (Cutter et al., 2003). The SVI approach enables relative vulnerability comparisons between communities and between geographical regions, which can aid in evaluating the susceptibility of communities to future hazardous threats. An enhanced understanding of the factors that determine vulnerability will also aid in identifying actions to reduce vulnerability (Adger et al., 2004).

This research utilized an SVI approach to examine the underlying socioeconomic, institutional, political, and cultural factors that determine how people within coastal Louisiana respond to a wide range of existing or hypothetical hazards events (Adger et al., 2004). The approach identified the presence and location of socially vulnerable groups in coastal Louisiana at the census block group level. This approach used both disaggregated and combined indicators to assess social vulnerability in coastal Louisiana at the census block group level. Construction of the coastal Louisiana SVI began with the selection of socioeconomic variables identified in the literature and derived primarily from the 2010 Census and the 2009-2013 American Community Survey (ACS). These variables were then synthesized using Principal Components Analysis (PCA) to identify significant components that represented broader categories of social and economic vulnerability. The components were then combined into a single index to assess relative social vulnerability for populated census block groups across the coast. The SVI of each census block group was then classified by standard deviation and mapped to identify locations ranging from high to low vulnerability.

3.0 Methods

3.1. Selecting Social Vulnerability Indicators

Vulnerability is a function of local socioeconomic conditions and the nature of the hazard to which the human population is exposed (Adger et al., 2004). While overall vulnerability is dependent upon exposure to specific hazards, social vulnerability represents the inherent characteristics of a community or population group that influence how it is able to respond to and recover from any number of theoretical hazards events. Many factors contribute to the ability of communities to respond adaptively to changing conditions and these factors can be represented by any number of indicator variables. Indicator variables are either quantitative or qualitative measures derived from observed facts that simplify the reality of complex situations (Cutter et al., 2010). This analysis utilized 37 key variables (as described below), directly related to the vulnerability factors, to derive the SVI. These variables were selected based on a review of existing literature, including the work of Cutter (2003), the State of Texas (Peacock et al., 2011), and US Army Corps of Engineers (Dunning & Durden, 2011) and were adapted to include factors specific to coastal environments (Hijuelos & Hemmerling, 2015; Jepson & Colburn, 2013).

Previous research has examined the relationship between social vulnerability and coastal storm events, identifying structural weaknesses of certain populations that highlight their specific vulnerabilities (Table 1). Because the root causes of these vulnerabilities (lack of financial resources, special medical needs, political disempowerment, etc.) are independent of any specific hazard, they can be adapted and considered across a range of hazardous events. In the case of coastal storms and other acute onset events, issues related to immediate evacuation are important. In the case of gradual onset events, such as coastal land loss and sea level rise, immediate evacuation may not be needed. Rather, issues related to population relocation become important. The same structural weaknesses of the vulnerable populations exist, regardless of the type of hazard or the speed of onset.

While certain factors such as poverty, minority status, and age are determinants of vulnerability across a wide spectrum of different hazards, other factors make communities more vulnerable to certain types of hazards. In resource dependent communities, for example, disruption of livelihoods can result from the loss of land and animals for farmers, or boats and nets for fishers (Wisner et al., 2004). As a result, high levels of natural resource employment are an important determinant of a coastal community's social vulnerability to the impacts of land loss, sea level rise, and tropical storm events.

Table 1: Social Vulnerability Factors and Their Implications During and After Coastal Storm Events (Adapted from Dunning & Durden, 2011).

Vulnerability Factor	Response During Event	Recovery
Low income/poverty level	Lack of resources may complicate evacuation	Lack of financial resources may hinder ability to recover
Elderly/very young	Greater difficulties in evacuation, increased health and safety issues, potential for higher loss of life	May lack ability to rebound
Disabled/special needs	Greater difficulties in evacuation, increased health and safety issues, potential for higher loss of life	Lack of facilities and medical personnel in aftermath may make it difficult to return
Single parent/female-headed households	Lack of resources and special needs relative to child care may complicate evacuation	Lack of resources may hinder ability to recover
Minorities	Lack of influence to protect interests, politically disempowered	Lack of influence to protect interests, lack of connections to centers of power or influence
Occupants of mobile homes/renters	Occupy more vulnerable housing	Potential displacement with higher rent
Natural resource dependence	Delays in evacuation to protect assets, resulting in health and safety issues, including potential for higher loss of life	Potential loss of property and assets may hinder ability to recover, livelihood deterioration

Data used to represent the key socioeconomic variables were extracted from the 2010 Census and the 2009-2013 ACS at the census block group level[1]. The block group is a census unit containing approximately 1,000 people, making it the smallest unit for which relatively complete socioeconomic data is available. While vulnerability varies on smaller scales, including the household level, the block group is the most practical unit that can be reliably quantified and is standardly utilized by local officials and public agencies. Whenever possible, a vulnerability or resilience assessment should include either point-level data or block group level data as these data can then be aggregated to larger geographical scales depending on the specific data needs of the study. Given that PCA requires large sample sizes, all populated census block

[1] The American Community Survey is an ongoing survey conducted by the U.S. Census Bureau that regularly gathers data previously gathered in the decennial census. At small census geographies, such as the census block group, data gathered by the American Community Survey exhibit high levels of sampling error. Sampling error is reduced when the data is aggregated into larger groupings (Hijuelos & Hemmerling, 2015).

groups within the 2017 Coastal Master Plan modeling domain were utilized in the analysis to ensure the underlying assumptions of the PCA were met. Generally, PCAs require sample sizes ranging from 5 to 10 samples per variable (Bryant & Yarnold, 1995; MacCallum et al., 2001; Nardo et al., 2005). As a result, analyses at smaller scales, such as individual parishes, would be limited to those that contain large numbers of block groups (e.g., Orleans Parish) and would require additional testing to ensure the assumptions of the PCA were met.

All input variables were normalized as percentages, per capita values, or density functions and then standardized using z-score standardization. Calculating z-scores allows for comparison of dissimilar data sets on a common scale, generating variables with a mean of 0 and standard deviation of 1. After all the data were transformed into the units required for analysis of each category, PCA was run on the variables to reduce the observed variables into a smaller number of significant components that represent broader categories of socioeconomic vulnerability.

3.2. Conducting Principal Components Analysis

PCA is a multivariate statistical technique generally used to extract the most important information from a large dataset, simplify the description of the dataset, and analyze the structure of the observations and the variables (Abdi & Williams, 2010). PCA analyzes inter-correlated dependent variables and creates new variables, called principal components that are linear combinations of the original variables. These components are surrogate variables that serve to simplify a large number of correlated variables. The analysis produces a correlation matrix in which each original variable is assigned a loading (i.e., weight) as a measure of the variable's correlation to each component. The loadings inform the relative importance of each of the original variables to the components identified in the PCA. In this analysis, variables were deemed important if the PCA resulted in a loading greater than or equal to 0.3. A value of 0.3 or above indicates multicollinearity, meaning that the predictor variables are highly correlated with one another (Hair et al., 1998). Variables that did not meet the threshold for any component were eliminated from the analysis and a new PCA was performed. Once it was determined that all variables met the loading threshold, the number of components to retain in the analysis for interpretation was decided. This decision was largely based on the total amount of variance accounted for by each component, as reported in the component's eigenvalue. In a PCA, the first component always accounts for the greatest amount of variation in the original variables. The second component is uncorrelated with the first and accounts for the maximum variation that is unexplained by the first component. Each subsequent component likewise accounts for the maximum variation not accounted for in the previous components, such that explained variation is additive with each successive component. Although the total number of possible components is equal to the total number of variables, only meaningful components that explain the majority of the variance are retained in a PCA. In this analysis, the Kaiser-Guttman criterion was used to select the number of components retained in the PCA, such that components with eigenvalues greater than 1 were considered meaningful and retained (O'Rourke et al., 2013). Because an eigenvalue is a measure of the amount of variance accounted for by a component and because the constituent variables are standardized, any component with an eigenvalue greater than 1 accounts for a greater amount of variance than any of the original variables.

Using the results of the PCA, variables with the highest loadings (> 0.3) within a component were identified as the most important, and these variables were then used to assign a descriptive label to the component. When necessary, a directional adjustment was applied to the entire component to assure that positive values indicated a tendency to increase vulnerability and negative values indicated a tendency to decrease vulnerability (Cutter et al., 2003). If a component exhibited positive high loadings for variables that would contribute to decreased vulnerability, the component value was multiplied by -1. Components in which the signs of the high loading variables were consistent with their contribution to social vulnerability (a positive sign if they increased vulnerability or a negative sign if they decreased vulnerability) required no adjustment. For components where the influence of the variables was ambiguous or bifurcated, the absolute value was used.

3.3. Calculating Overall Vulnerability

While understanding the distribution of individual social vulnerability components can be useful, it is often helpful to assess overall social vulnerability if the multidimensional components can be combined into a single index (Rygel et al., 2006). Using the results from the PCA, the components were combined to derive a SVI for all populated census block groups within the study area. Indices are theoretical constructs in which two or more components of are combined to form a single summary value. Such indices have been used in hazards research to generate new information that can be used to comparatively assess differences in social vulnerability in given geographical units (Clark et al., 1998; Cutter et al., 2003; Wu et al., 2002).

The directionally-adjusted components in this study were assigned the percentage of their respective eigenvalues, or variance explained, as weights using the following equation:

$$W_i = \frac{l_i}{\sum l_i} \tag{1}$$

where W_i is the weight assigned to each component, and l_i is the eigenvalue, or variance explained, of each component.

Assigning weights to each component based on the variance explained is reasonable because a larger eigenvalue represents a larger share of the total variance and a more important component (Wang, 2009). Thus, the first component explains the most variance and each successive component contributes less to the variance explained. The final SVI value was calculated using the following equation:

$$F_s = \sum(F_i * W_i) \tag{2}$$

where F_s is the census block group level SVI value, F_i is the component value for each component, and W_i is the weight assigned to each respective component (1).

The resultant social vulnerability values represent a relative measure of social vulnerability and not an absolute measure (Cutter et al., 2011). To graphically represent the relative nature of the metric, the weighted social vulnerability values were normalized by z-scores and mapped by census block group to form a distribution with a mean of 0 and standard deviation of 1. Census block groups with SVI values greater than one standard deviation from the mean have previously been classified as vulnerable (Cutter et al., 2003). For this analysis, five categories of vulnerability were identified: low, medium low, medium, medium high, and high. Medium values are within one standard deviation of the mean, medium low values are between -1 and -1.96 standard deviations, medium high values are between 1 and 1.96 standard deviations, and high and low values are those greater than 1.96 or less than -1.96 standard deviations from the mean, respectively. A z-score of 1.96 indicates that the respective index value is significantly above or below the mean value (alpha = 0.05). Finally, the census block level values were aggregated and mean parish-level index values were calculated. Both the census block group and the parish index values allow for a ranking of vulnerability relative to the parish average.

4.0 Results

4.1. Principal Components Analysis

The initial 37 variables were analyzed using PCA. One variable (the percent Native American population) did not load significantly on any of the components and was not included in the final PCA run. The final 36 variables representing social vulnerability were grouped into eight components based on the Kaiser-Guttman criterion. In total, most of the variance explained was captured by economic status (20.3%), rural population (14.4%), and age/dependent population (9.5%). The remainder of the variance explained by each component can be found in Table 2.

There are several variables that have split loadings, meaning that they load onto more than one factor. As each of these variables has loadings greater than 0.3, they can be interpreted as contributing to more than one factor. These split loadings (sometimes referred to as complex structures) are not uncommon in the PCA and are not a problem if the components are interpretable. The percentage of the population in nursing homes is one item that has a split loading. It loads onto both component 6 "nursing home residents" and component 7 "disabled, dependent population." This is explained by the fact that nursing home residents are often either elderly or disabled, two groups that are at times mutually exclusive. Similarly, the percent of renter-occupied housing units loads on both component 1 "economic status" and component 5 "extractive industry employees." Here, for example, the percent of renters in areas with high resource extraction employment is indicative of the number of non-local and out-of-state workers employed in the oil and gas industry. In other locations, however, a lack of home ownership is more indicative of lower economic standing.

Directional adjustments were made on several components, as shown in Table 2. For the disabled population component, the three constituent variables (proportion of the population that is disabled, receiving social security, and residing in nursing homes) had negative loadings. Because the signs of the high loading variables must be consistent with their contribution to social vulnerability, with positive values indicating increased vulnerability, the overall component score was multiplied by -1. The same adjustment was made to the nursing home population. Finally, both young children and elderly residents are considered socially vulnerable. Therefore, the component comprised of age-related variables was considered non-directional and an absolutely value adjustment was used. This assures that areas with high levels of elderly population and areas with high numbers of young children are each classified as vulnerable.

Although general descriptive component labels are applied during the interpretation of each component, more variables load highly onto those components than the labels can express (Rygel et al., 2006). For example, the first component was interpreted as "economic status" because the percent of the population living in poverty and per capita income loaded highest on it. This component also included high percentages of African American residents and the number of female headed households, categories that were statistically correlated with economic status. Similarly, the percentage of mobile homes and the number of hospitals in close proximity were strongly correlated with rural populations. Each of the other components was similarly interpreted. Populations more likely to be dependent upon others due to age included those over 65 years of age and those less than five years of age. These populations were also closely correlated with average household size and the percentage of the population receiving Social Security income. The non-English speaking, migrant component included the percentage of the population speaking little or no English as well as the percentage of the population born outside of the United States. Within the study area, these populations also correlated closely with the Hispanic population.

Two other components included an aspect of natural resource dependence. The first broad category of natural resource dependence included individuals employed in forestry, agriculture, and fisheries as well as those employed in oil and gas extraction. These populations were closely correlated with several housing categories, including the percentage of renters in a community and the number of vacant housing units. The second natural resource-related component included locations with a high Asian population. In this component, this population was strongly correlated with the percentage of the population employed in forestry, agriculture, and fisheries.

The percentage of the population residing in nursing homes loaded strongly on two components. In one instance, the percentage of the population residing in nursing home was the single dominant component. In the next component, the percentage of the population residing in nursing home was closely correlated with the percent of the population that is disabled. This suggested that we were looking at two different population groups, one that was dominated by nursing home residents in general and another that included a large proportion of disabled residents.

Table 2: Cardinality and Component Loading for Each Principal Component.

Component	Directional Adjustment	Variance Explained	Component Interpretation	Dominant Variables	Component Loading
1	+	20.2%	Economic Status	Percent of population living in poverty	0.8
				Percent African American population	0.8
				Percent of households that have no vehicles	0.7
				Percent of female headed households	0.7
				Percent renter-occupied housing units	0.6
				Percent of labor force that is unemployed	0.6
				Percent of households receiving Supplemental Social Security income	0.6
				Percent of population 25 years or older with no high school diploma	0.6
				Percent single parent households	0.3
				Percent of population employed in service industries	0.4
				Percent of adult population that is	0.4

Component	Directional Adjustment	Variance Explained	Component Interpretation	Dominant Variables	Component Loading
				disabled	
				Percent vacant housing units	0.4
				Percent of households receiving public assistance	0.4
				Percent of population participating in civilian labor force	-0.5
				Per capita income in dollars	-0.7
				Percent households making more than $75,000	-0.8
2	+	14.4%	Rural Population	Percent mobile homes	0.6
				Percent rural population	0.6
				Percent of population employed in mining and petroleum extraction industries	0.4
				Median value of owner-occupied housing in dollars	-0.5
				Heath facilities within 20 mile radius	-0.7
				Housing density, number of households per square mile	-0.7
				Population density, number of persons per square mile	-0.7
3	||	9.5%	Age, Dependent Population	Percent of population over 65 years of age	0.7
				Median age	0.7
				Percent of households receiving Social Security income	0.6
				Percent in poverty and over 65 years of age	0.4
				Average persons per household	-0.5
				Percent of population under 5 years of age	-0.5

Component	Directional Adjustment	Variance Explained	Component Interpretation	Dominant Variables	Component Loading
4	+	6.8%	Non-English Speaking, Migrant	Percent of population over 5 years of age that speak little or no English	0.7
				Percent of population born outside of the United States	0.7
				Percent Hispanic Population	0.6
5	+	4.3%	Natural Resource Dependent Communities	Percent vacant housing units	0.3
				Percent of population employed in forestry, agriculture, and fisheries industries	0.3
				Percent of population employed in mining and petroleum extraction industries	0.3
				Percent renter-occupied housing units	0.3
				Percent mobile homes	0.3
				Percent of households receiving Social Security income	-0.3
6	–	3.4%	Nursing Home Residents	Percent of population participating in civilian labor force	-0.3
				Percent of population in nursing homes	-0.5
7	–	3.1%	Disabled, Dependent Population	Percent of households receiving public assistance	-0.3
				Percent of adult population that is disabled	-0.4
				Percent of population in nursing homes	-0.6
8	+	2.9%	Asian, Natural Resource Employees	Percent Asian population	0.5
				Percent of population employed in forestry, agriculture, and fisheries industries	0.4

Figures 1 through 8 depict each of the significant components at the block group level in the study area. The 1,647 census block groups were sorted into five categories of vulnerability by standard deviations above or below the mean, as previously described.

For the economic status component, the most socially vulnerable block groups are located in the coastal zone's densely populated urban areas, with the highest levels of vulnerability located in the New Orleans metropolitan area (Figure 1). Conversely, suburban block groups located outside of the urban cores of the region generally exhibit lower degree of economic vulnerability.

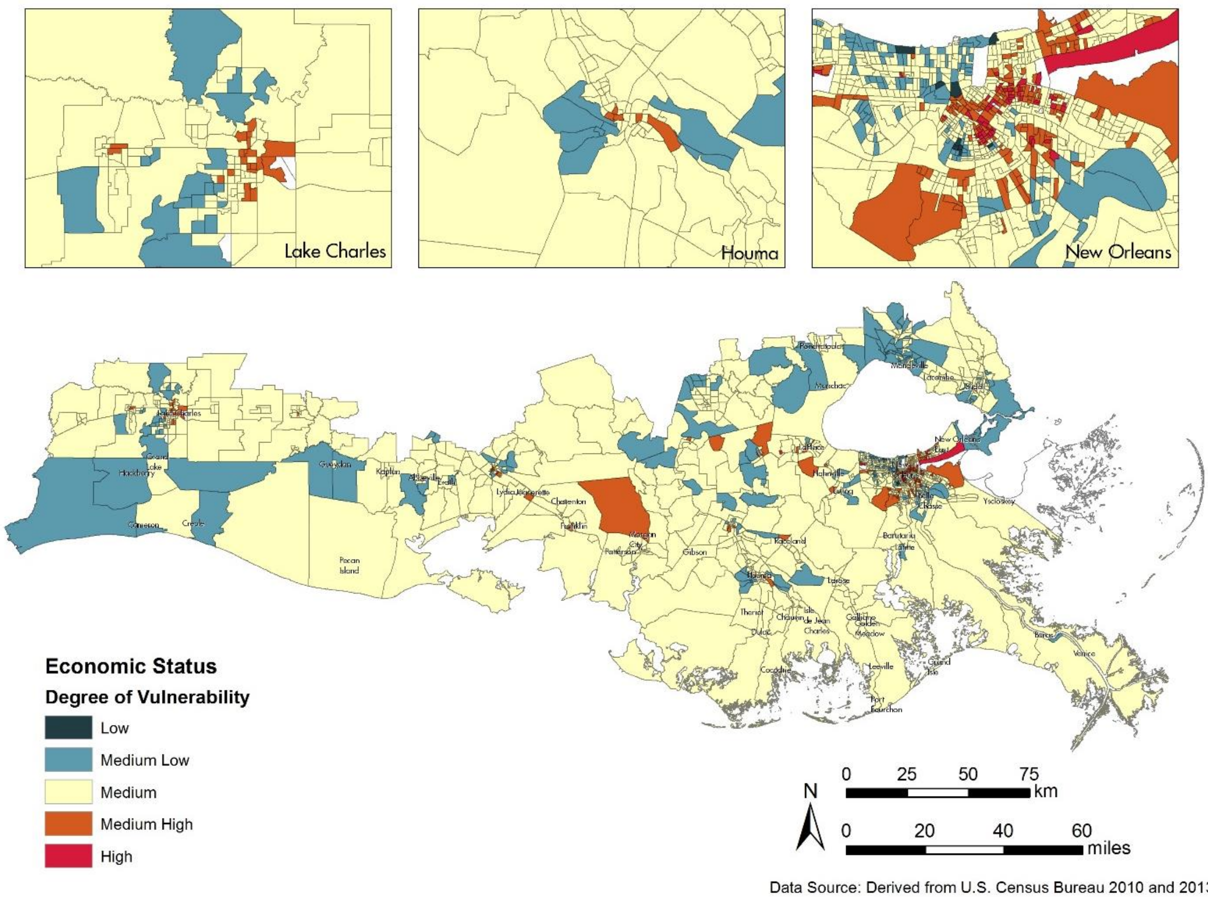

Figure 1: Economic Status Component Values (Component 1; 20.3% of Variation), Displayed as Standard Deviations from the Mean Component.

Just as urban areas show exceptionally high levels of social vulnerability, many aspects of rural life in coastal Louisiana are a cause of increased social vulnerability (Figure 2). Rural areas generally have a dispersed population that are often difficult to communicate with and evacuate when emergency events occur. People in these areas also are more likely to reside in mobile homes that are of more fragile construction and more vulnerable to high winds and flowing waters than traditional dwellings (Dunning & Durden, 2011). Lastly, rural residents generally have reduced access to medical facilities. For many of these reasons, census block groups with high levels of dependent populations, including very young children and the elderly, tend to concentrate in more developed areas, including large cities and towns, away from the coast (Figure 3).

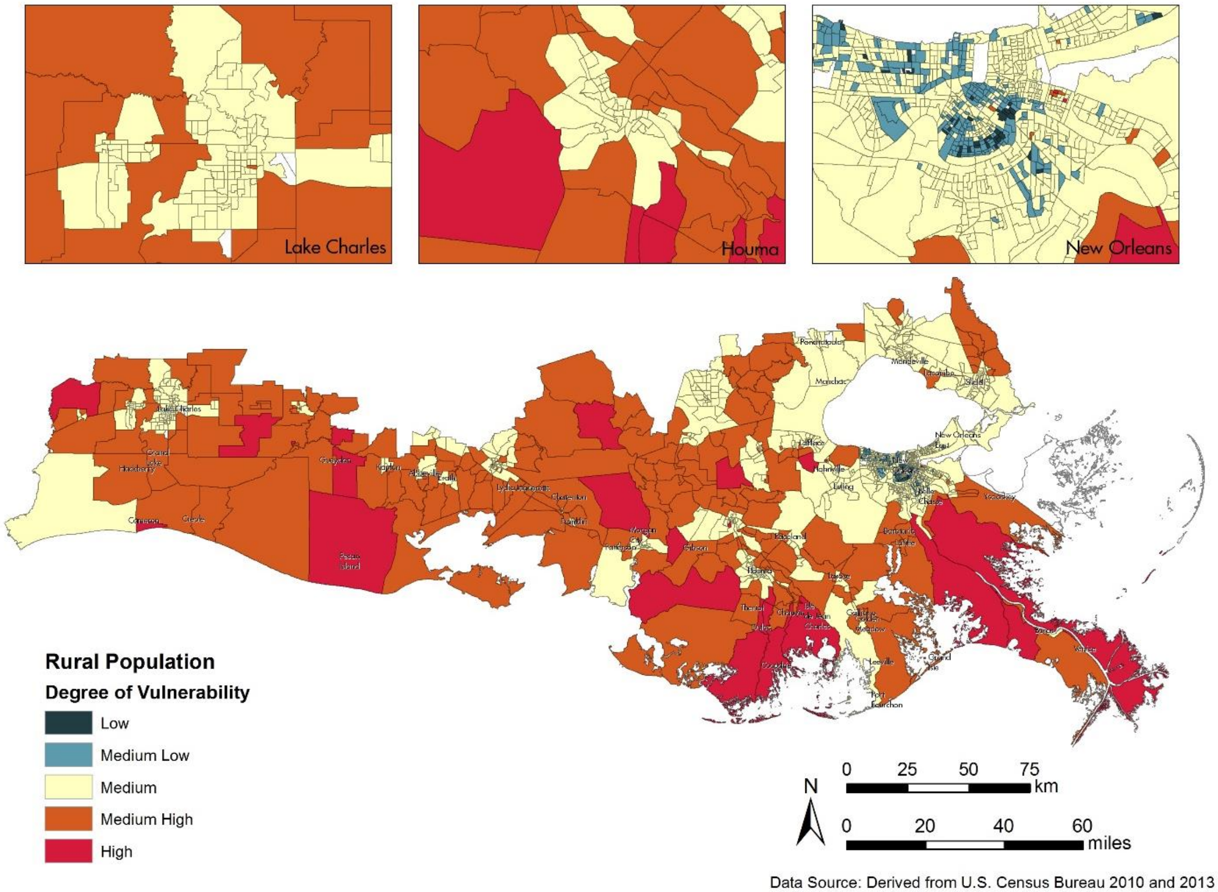

Figure 2: Rural Population Component Values (Component 2; 14.4% of Variation) Displayed as Standard Deviations from the Mean Component.

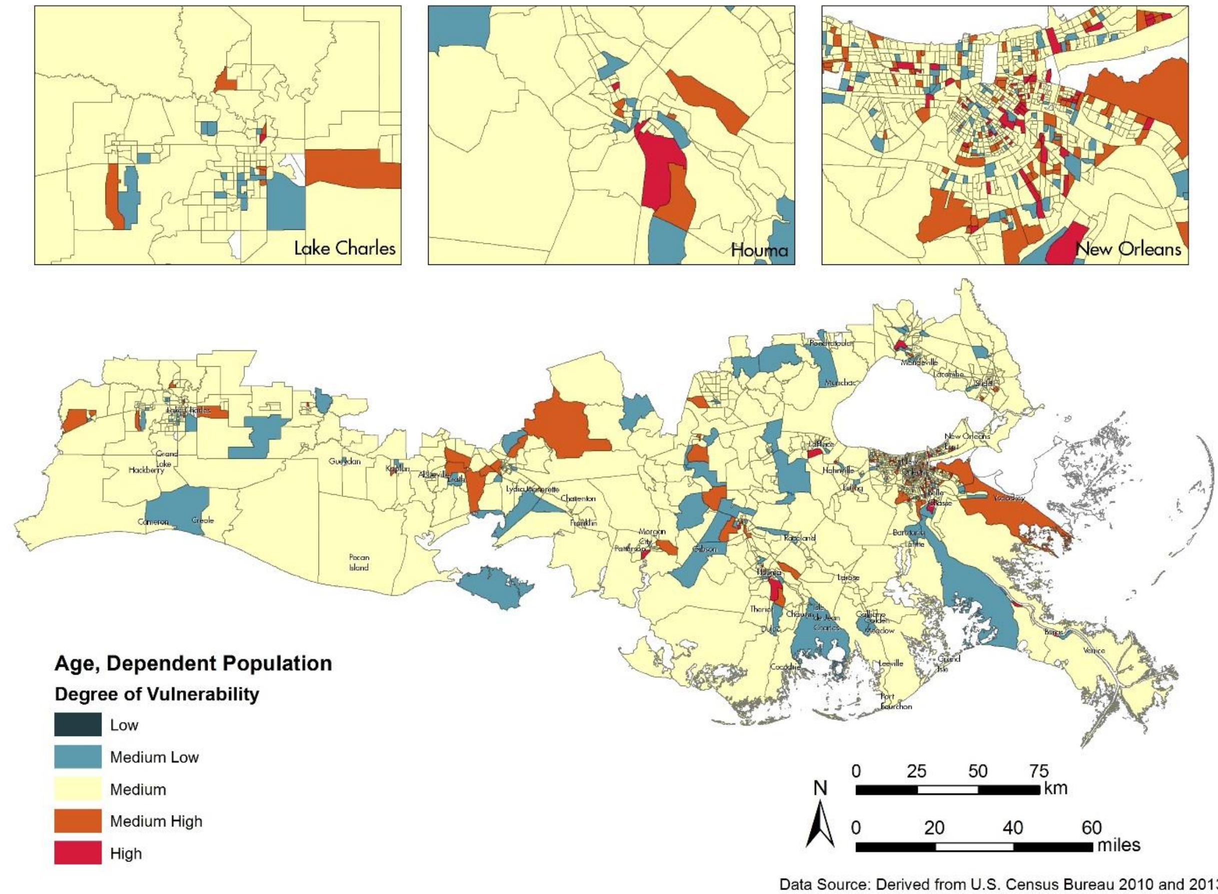

Figure 3: Age, Dependent Population Component Values (Component 3; 9.5% of Variation) Displayed as Standard Deviations from the Mean Component.

Conversely, much of the non-English speaking and foreign-born populations, largely Hispanic, reside in a number of clusters within Louisiana's coastal zone (Figure 4). This population tends to be more widely dispersed across the coastal zone, with both an urban and rural component. The urban component is centered on New Orleans while the coastal foreign-born population is located in coastal shoreline parishes, such as Vermilion, Terrebonne, Lafourche, Plaquemines, and St. Bernard. Many of these same areas are home to high numbers of residents reliant upon natural resource-related industries, such as petroleum extraction and fisheries, for their livelihoods (Figure 5). The highly clustered nature of these populations (both high and low) is indicative of the spatial dependence of the population on the location of the natural resource itself. Populations employed in natural resource extraction are more likely to reside in close proximity to that resource. Although these populations are often less likely to require any type of public assistance or social security income, they also tend to be more transient, signified by a higher number of renter-occupied housing units. This combination highlights the economic vulnerability of communities without a highly diversified employment base.

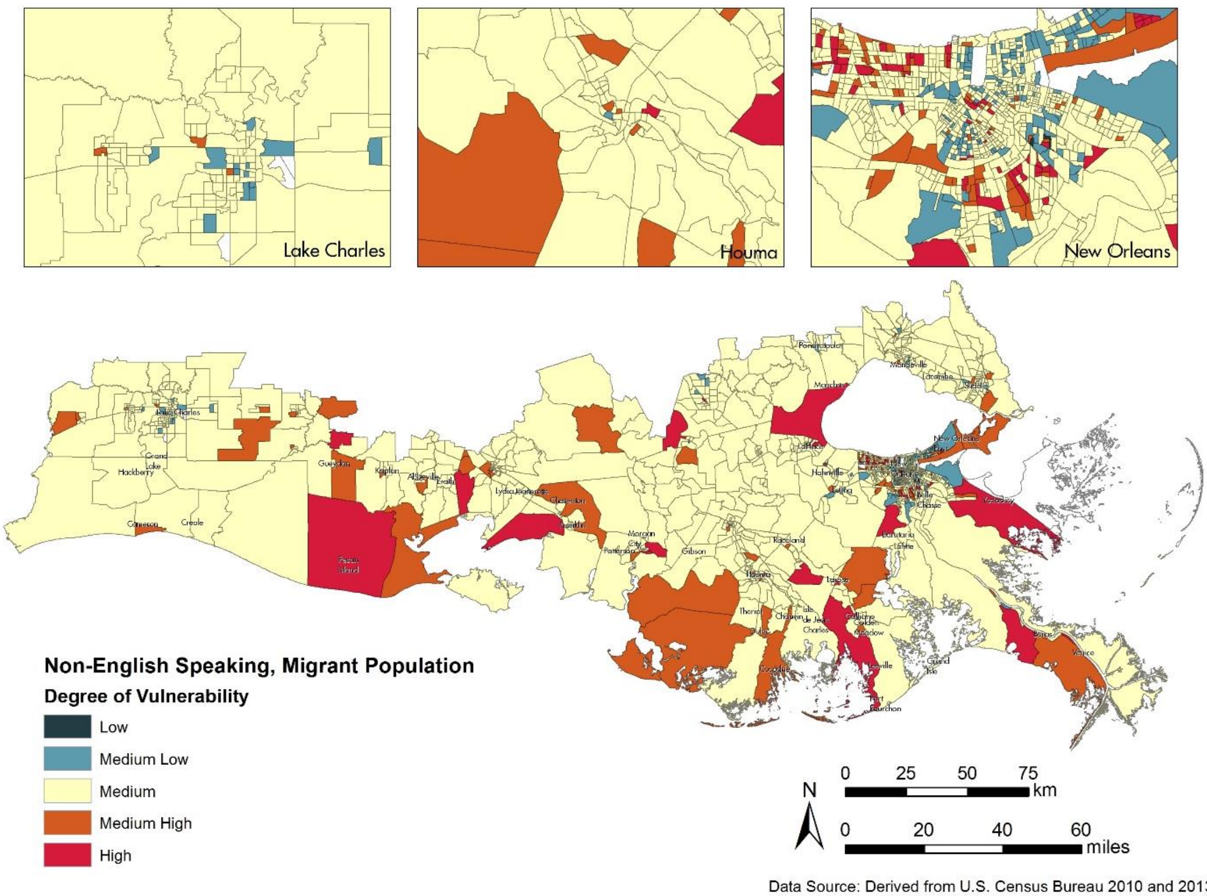

Figure 4: Non-English Speaking, Migrant Population Component Values (Component 4; 6.8% of Variation) Displayed as Standard Deviations from the Mean Component.

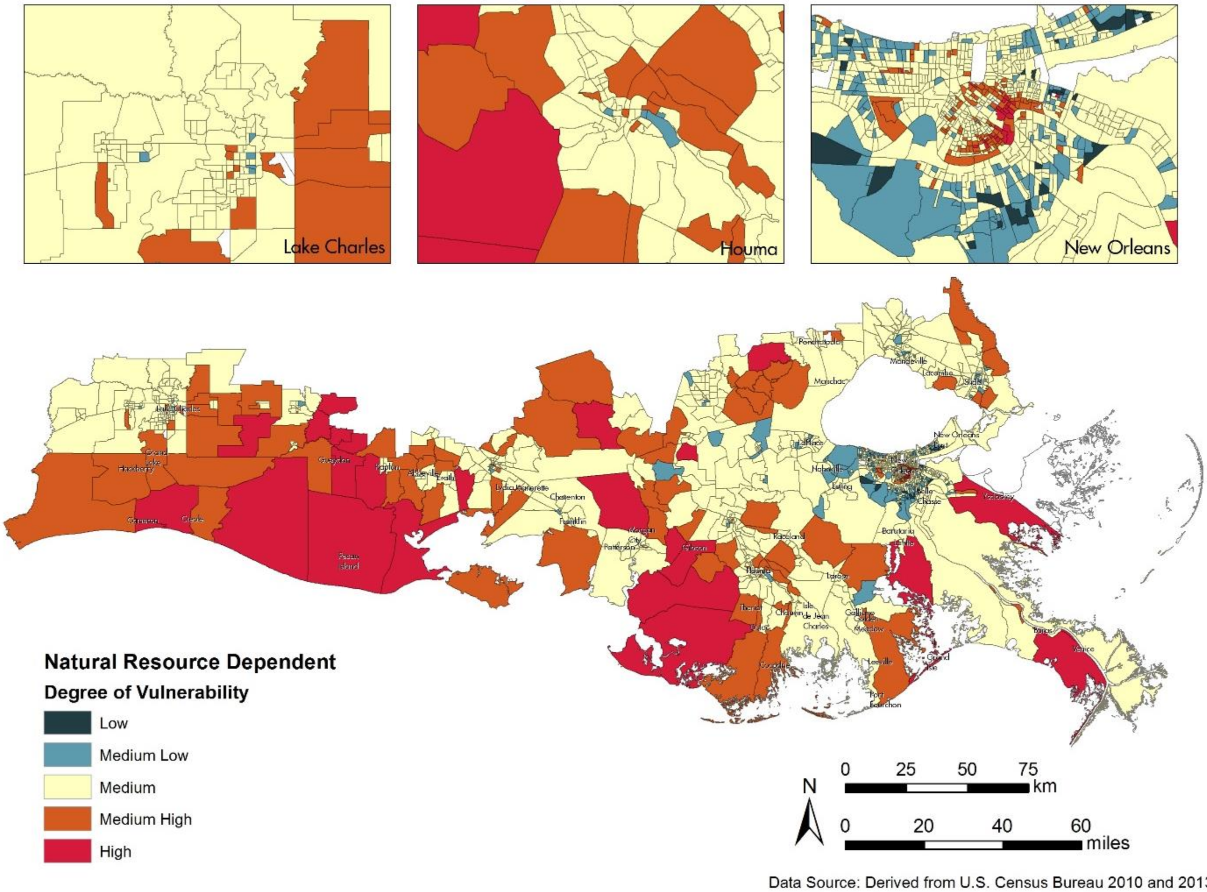

Figure 5: Natural Resource Dependent Population Component Values (Component 5; 4.3% of Variation) Displayed as Standard Deviations from the Mean Component.

Dependent populations residing in nursing homes (Figure 6) and the disabled population, many of whom also reside in nursing homes (Figure 7), are dispersed across the study area, mostly in cities and small communities. For the most part, these populations reside significantly away from the coastal zone and away from rural areas with the exception of coastal Lafourche Parish, which has a slightly elevated number of disabled residents compared to other coastal shoreline parishes. Additionally, there are far more disabled residents residing in assisted care facilities in metropolitan areas than there are elderly nursing home residents.

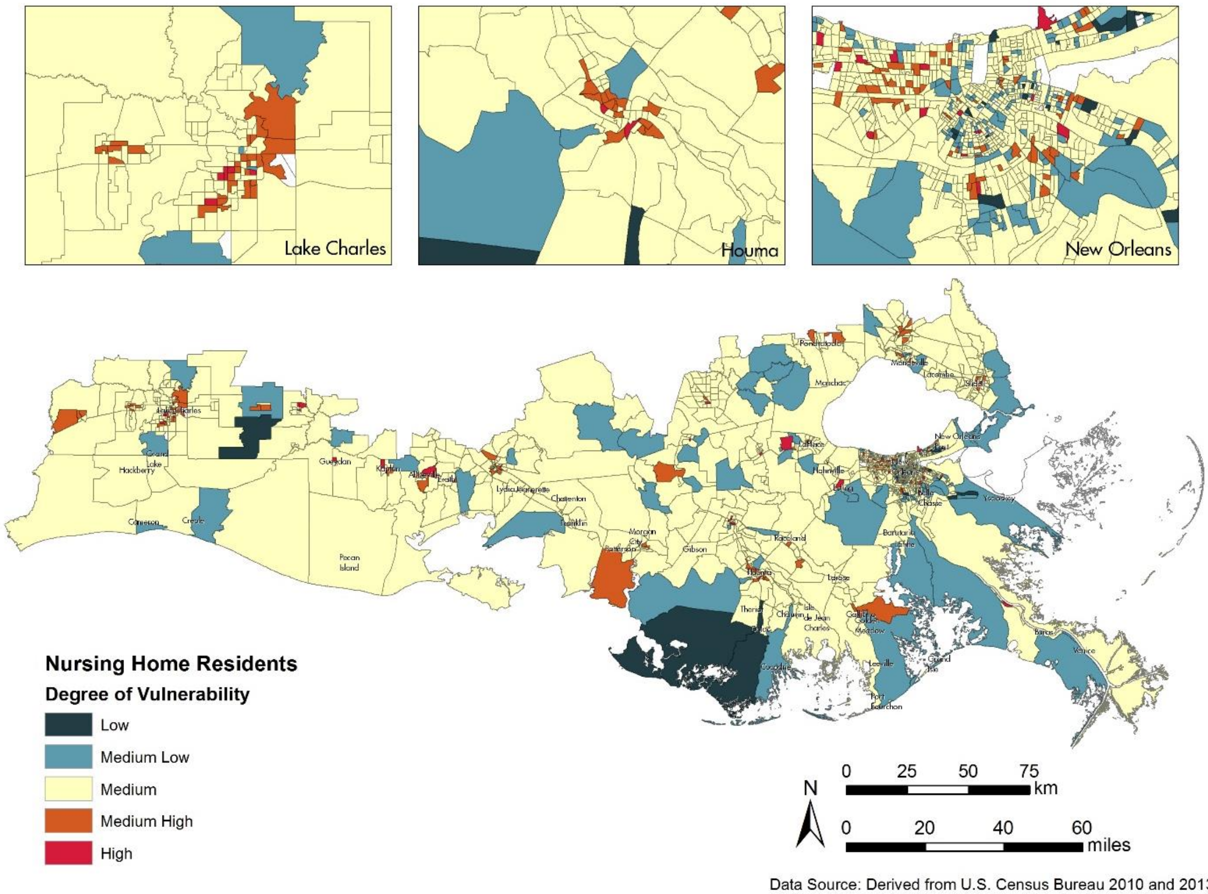

Figure 6: Nursing Home Resident Component Values (Component 6; 3.4% of Variation) Displayed as Standard Deviations from the Mean Component.

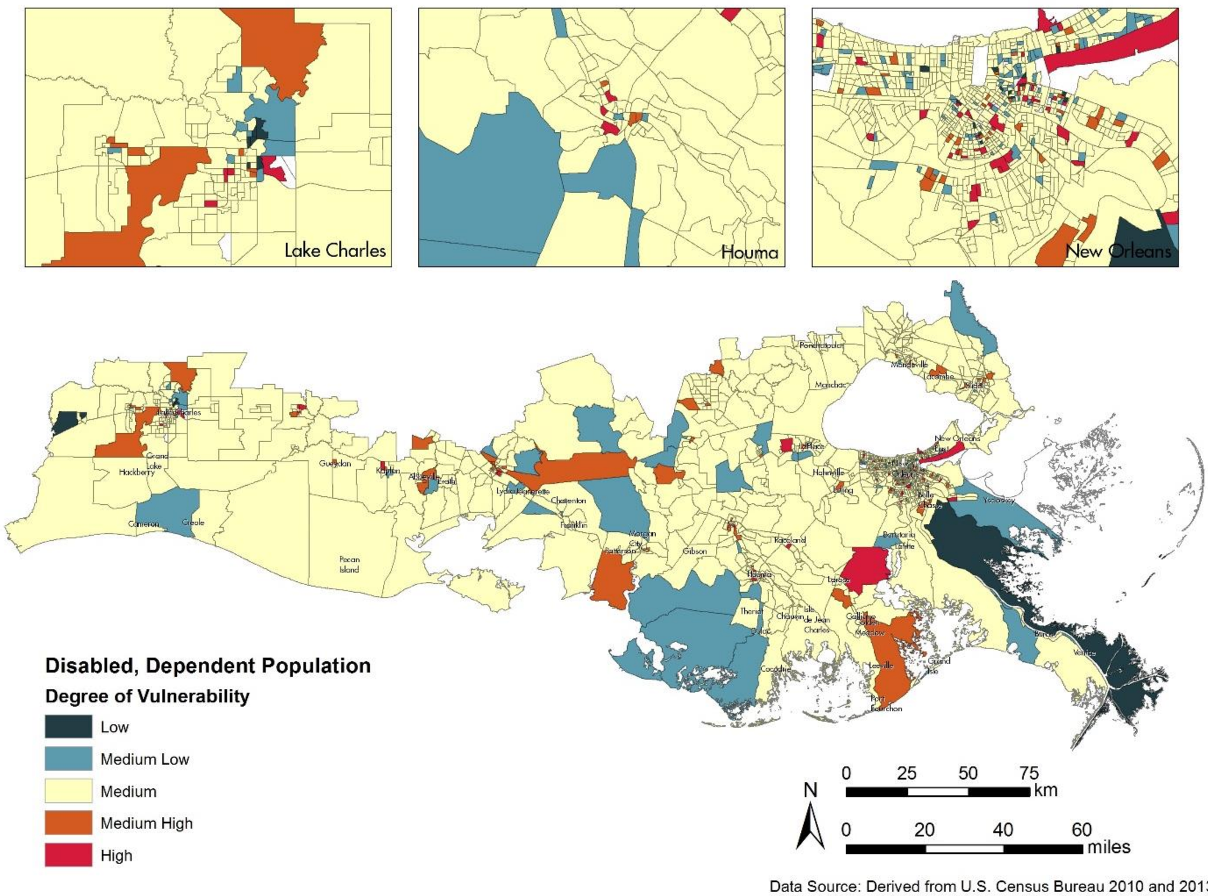

Figure 7: Disabled, Dependent Population Component Values (Component 7; 3.1% of Variation) Displayed as Standard Deviations from the Mean Component.

Finally, the PCA analysis highlighted a number of census block groups in which the percent Asian and the percent employed in the agriculture and fisheries were highly correlated (Figure 8). These census block groups are located in southern Plaquemines and western Terrebonne Parishes. Significantly, a high number of census block groups show exceptionally high component values on the outskirts of New Orleans, in New Orleans East, Belle Chasse, and on the West Bank of the Mississippi River.

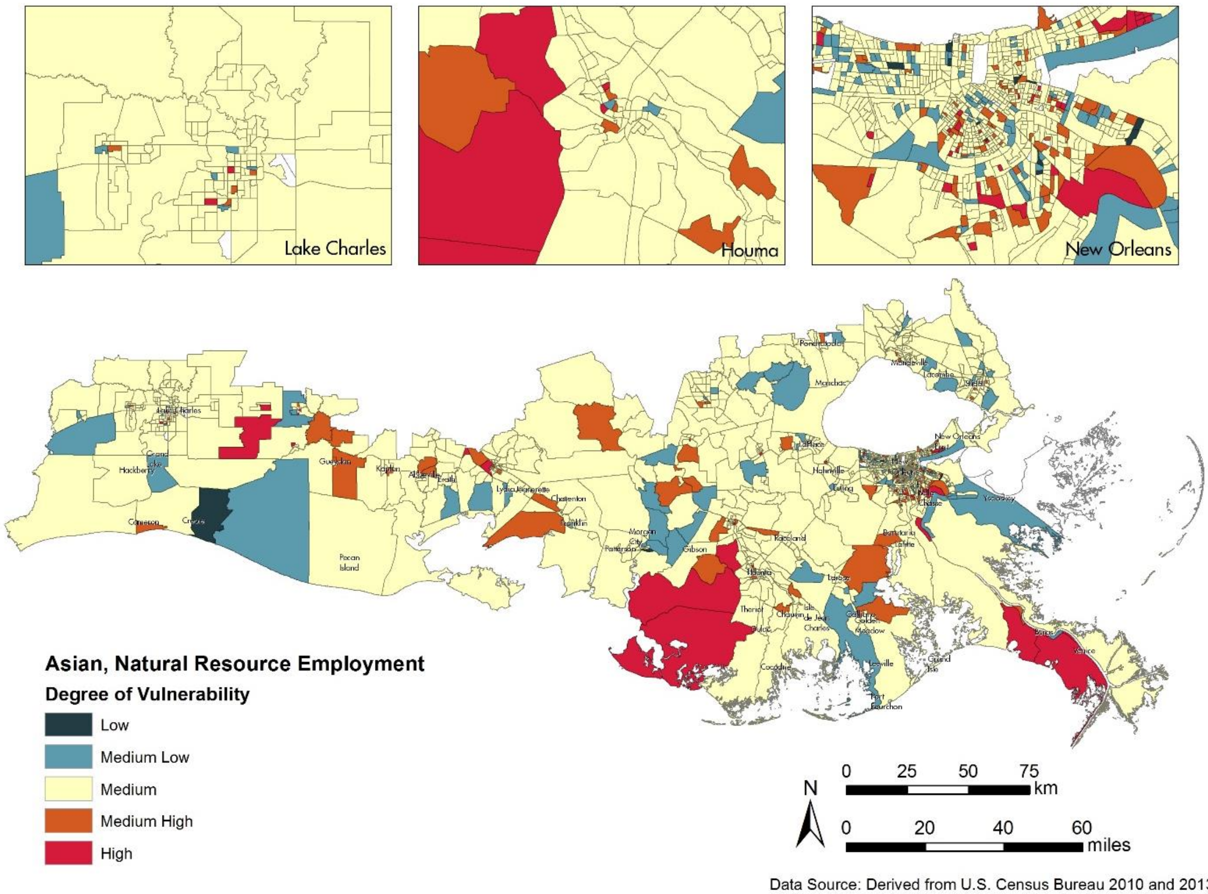

Figure 8: Asian, Natural Resource Employment Component (Component 8; 2.9% of Variation) Values Displayed as Standard Deviations from the Mean Component.

4.2. Social Vulnerability Index Values

The results of the PCA assigned a component value for all eight principal components to each census block group in the study area. These values were adjusted for cardinality and weighted (1). The final additive model (2) was used to derive the overall socio-economic vulnerability value for each census block group, F_S, as follows:

$$F_s = (F_1 * W_1) + (F_2 * W_2) + |F_3 * W_3| + (F_4 * W_4) - (F_5 * W_5) - (F_6 * W_6) + (F_7 * W_7) + (F_8 * W_8) \quad (3)$$

As with the individual components, the SVI values were mapped and areas ranging from high to low vulnerability were identified across the coast (Figure 9). The western portion of the study area generally has low to moderate levels of social vulnerability, while portions of the central coast and southeast Louisiana have medium high to high levels of social vulnerability. Many of these areas are those that are both rural and reliant upon natural resources, such as Plaquemines, St. Bernard, and Terrebonne parishes. The metropolitan census block groups within the study area, including New Orleans, Houma, and Lake Charles, show a bifurcation of social vulnerability, with areas of both high and low vulnerability in close proximity. This is especially apparent in the New Orleans metropolitan area, which contains census block groups with exceptionally high and low vulnerability values.

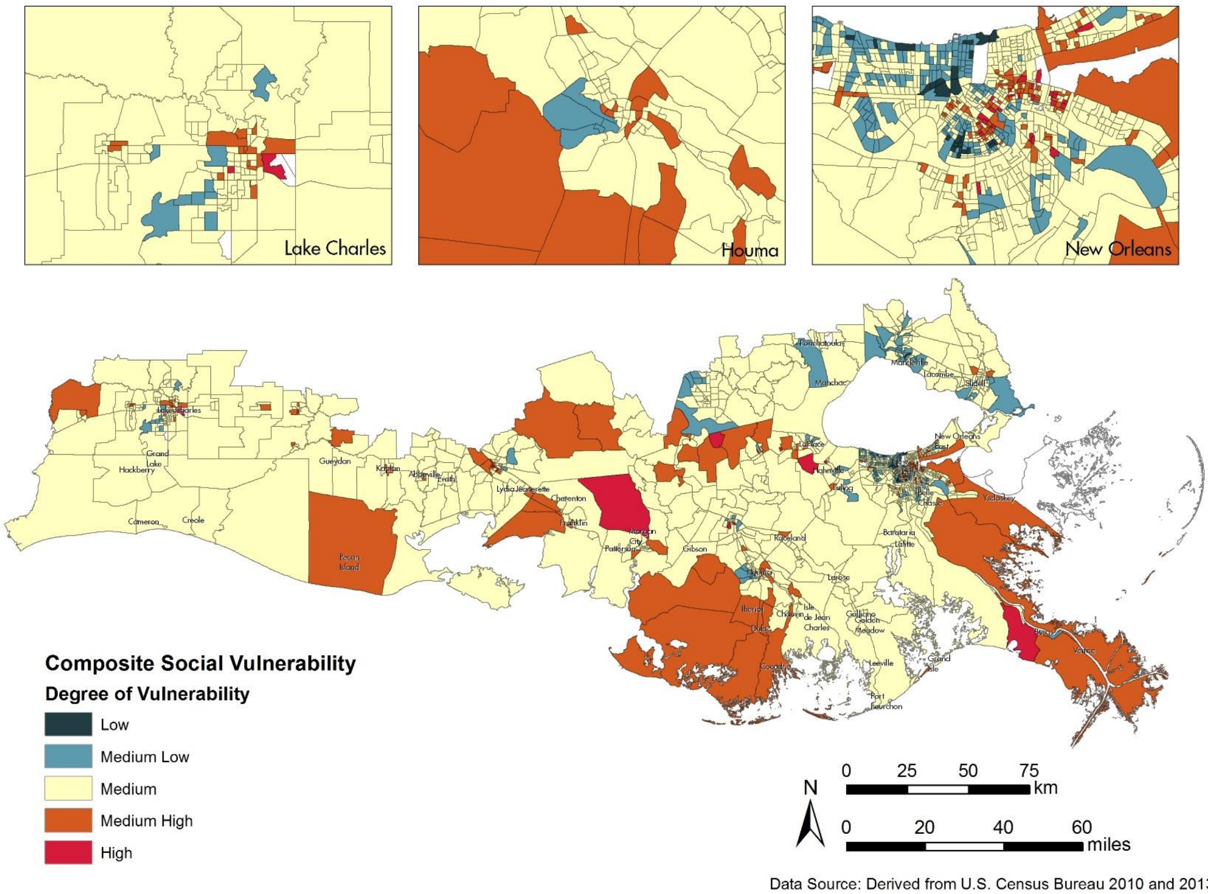

Figure 9: Social Vulnerability Index Values Calculated by Weighting and Summing Each Component Value and Displayed as Standard Deviations from the Mean Component Value.

When the SVI values were averaged and analyzed at the parish scale, all parish means were within one standard deviation from the coast wide mean, indicating that much of the variability observed at the block group level was masked when aggregated to the parish level. The bifurcation of social vulnerability in the urban areas observed in Figure 9 and described above can be seen statistically in the range and standard deviation values at the parish level (Figure 10). Orleans Parish, which contains the entirety of the city of New Orleans, has a mean social vulnerability value only slightly higher than the coast wide average. However, it also has the greatest range of values and the highest standard deviation of all of parishes within the study area. It is important to note that some parishes are only partially included in the study area. Lafayette Parish, for example, only has four census block groups within the study area. Thus, the city of Lafayette itself is not included in the parish totals. Analysis of the parish level values also show that parishes with the lowest level of social vulnerability tend to be those suburban parishes surrounding the larger metropolitan areas, particularly those along the north shore of Lake Pontchartrain (St. Tammany and Tangipahoa) and those along the Interstate 10 corridor between New Orleans and Baton Rouge (Jefferson, St. Charles, and Ascension; Figure 10). Overall, parishes with the highest levels of social vulnerability tend to be more rural, bordering the Gulf of Mexico or bordering the Atchafalaya Basin.

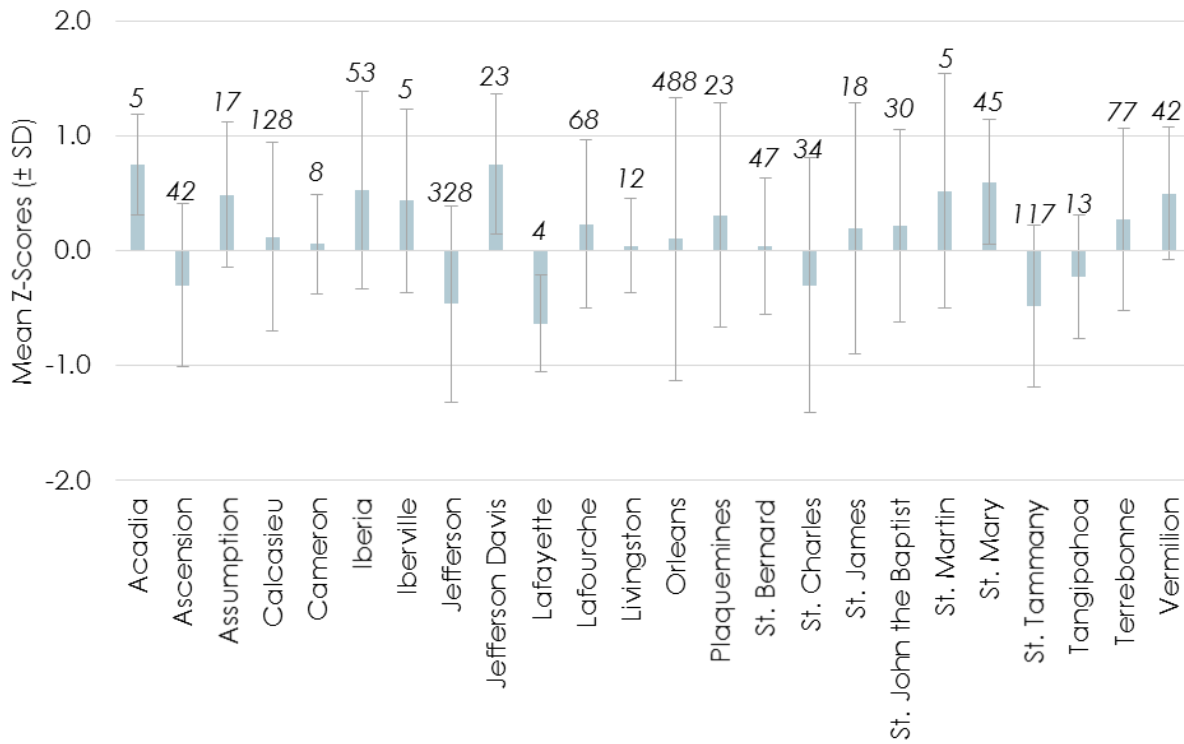

Figure 10: Social Vulnerability Index Z-Scores Averaged Across Census Block Groups for Each Coastal Louisiana Parish Within the Master Plan Domain. The coast wide mean has a z-score equal to 0, such that mean parish scores less than 0 are less vulnerable than those greater than 0, relative to the coast wide mean. Numbers in italic above the standard deviation bars refer to the sample size (i.e., number of block groups) of each parish.

5.0 Conclusion

While all residents of coastal areas, particularly those residing in flood hazard areas, are at risk, the social impacts of hazard exposure often fall disproportionately on the most vulnerable people in a society, including the poor, minorities, children, the elderly, and the disabled. These groups often live in the highest-risk areas and have the fewest resources to prepare for a hazards event (Dunning & Durden, 2011). The SVI calculated for coastal Louisiana offers valuable insights into the social and economic conditions that increase community vulnerability to hazards events. The particular characteristics of social vulnerability in coastal Louisiana – economic status, rural population, age, non-English speaking, natural resource dependence, nursing home residents, the disabled, and minority groups employed in natural resource extraction – will need to be considered in any future planning efforts. Monitoring change in social vulnerability, both in terms of the relative importance of individual variables and the broader components, can be conducted over time as new data becomes available. Further, by examining the spatial distribution of these social vulnerability components, at both the individual component and combined index levels, this research can enable a greater understanding of social vulnerability factors that can be used in the planning process to anticipate and plan for hazard events (e.g., extreme weather events), evaluate management measures, and evaluate project alternatives. Knowing the location of socially vulnerable communities will allow planners to more effectively target and support efforts to mitigate and prepare for disaster events. First responders can plan more efficient evacuation of those people who might require special assistance, such as the elderly and residents who do not speak English well. Local governments can identify neighborhoods that may need additional human services support in the recovery phase or as a mitigating measure to prevent the need for the costs associated with post-response support (Flanagan et al., 2011). This SVI enables an assessment of the relative vulnerability of communities and can be used to further interpret the findings of other master plan metrics (e.g., support for traditional fishing communities). For example, the metric results or their components could be summarized by community according to the level of vulnerability assigned to that community and then compared across the vulnerability categories to evaluate whether there are disproportionally lower (or higher) scores in vulnerable communities. Results of an example of such an assessment are described in Attachment C4-11. Providing community level information to the Planning Tool could support further evaluation of how communities with different levels of vulnerability may be affected by projects or alternatives.

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