Development of Social Indicators of Fishing Community Vulnerability and Resilience in the U.S. Southeast and Northeast Regions

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http://www.st.nmfs.noaa.gov/humandimensions/social-indicators/index

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III. Abstract

Viable measures of social well-being and sustainability, including measures of vulnerability and resilience, are needed for coastal fishing communities. Although sustainable development indices have been created and implemented at national and regional levels, few are available at the local or community level, and even fewer address the social aspects of U.S. fisheries. We developed a suite of social indicators for use in fisheries social impact assessment (SIA). Data from more than 2,900 coastal communities in 19 states from Maine to Texas were used to create 14 social vulnerability and fishing dependence indices. Each index was developed using a factor analysis of secondary data obtained primarily from government sources, supplemented by a few private sources. The availability of these secondary data ensure replicability and feasibility under the time constraints usually available for completing social impact assessments for fishery management plans. Using cluster analysis, we selected a group of 20 communities to evaluate all 14 indices of social vulnerability. These indices can be used for cross-community and cross-regional comparisons, and will eventually be incorporated into social impact assessments of all U.S. marine fisheries.

IV. Acknowledgements

We have many people to thank for their help and support with this research and producing this technical memorandum. We would like to especially thank Rita Curtis, NOAA Fisheries, ST5 for her support of this work and continuing interest in our endeavors. With Rita's assistance and offer of a rotational detail, our work was greatly enhanced. We would like to thank the reviewers of this memorandum for their conscientious and thorough review of this document and to Trish Clay for her voluntary informal review that was so helpful. For her countless hours of data manipulation,we would like to thank Changhua Weng who turned those data files around in quick fashion. We would also like to thank Tarsila Seara for her extensive literature review that helped us frame the concepts. Also, for their contributions we would like to thank Julie Olson, Christina Package, Kari MacLauchlin, Ava Lasseter, and Brent Stoffle. Certainly, we appreciate the thoughtful comments and assistance from all of our workshop participants in both venues. And finally, for their continuous expert advice we would like to say a special thanks to Steve Jacob and Richard Pollnac; especially to Steve for his patient tutoring in factor analysis and willingness to be on call for anything statistical from the beginning.

V. Introduction

A. Background

With the growing emphasis on ecosystem-based management, there is an expanding need for measures of social well-being and sustainability, including resilience and vulnerability, for coastal fisheries and fishing communities. Because primary data collection is time consuming and costly, use of secondary data is a practical alternative that can provide substantial cost savings in developing these measures. The use of secondary data in the human dimensions of fisheries management is rapidly expanding. Community profiles, social impact assessments, determination of fishing dependence, and assessments of natural disasters are a few of the growing number of areas using secondary data. Here we explore the use of secondary data in the development of social indicators to measure fishing community vulnerability.

NOAA Strategic Plan

In the United States (US), the National Oceanic and Atmospheric Administration (NOAA)'s vision of the future is one of healthy ecosystems, communities, and economies that are resilient in the face of change. Ecosystems, communities, and economies can maintain and improve their resilience, health and vitality over time by anticipating, absorbing, and diffusing change—whether sudden or prolonged. This vision of resilience will guide NOAA and its partners in a collective effort to reduce the vulnerability of communities and ecological systems in the short term, while helping society avoid or adapt to long-term environmental, social, and economic changes. To this end, NOAA will focus on four long-term goals within its primary mission. The goals of Healthy Oceans and Resilient Coastal Communities (NOAA Strategic Plan, 2010) are the primary focus of this analysis, especially with regard to providing coastal decision-makers with accurate and reliable tools to apply toward reducing the vulnerability of their communities.

Ecosystem Based Management and Community Well-being and Sustainability

The use of indicators to monitor sustainability and other measures of well-being for all components of marine fisheries has long been promoted within international fisheries management (FAO 2008). Currently, US Fishery Management Plans (FMPs) have numerous measures of well-being and sustainability of fish stocks, but fewer of fishermen and their communities, though see GMFMC (2004; 2005) and PFMC (2006). Since the addition of National Standard 8 (16 U.S.C. § 1851(a)(8)) with the 1996 reauthorization of the Magnuson-Stevens Fishery Conservation and Management Act (16 U.S.C. § 1801 et seq.), all NOAA Fisheries regions have developed community profiles which required census and fisheries data to be assembled at the place level. Yet, there have been only a small number of attempts to utilize these data in an empirical approach to quantify aspects of well-being and sustainability of fishing communities. Two examples are a vulnerability index for fishing communities (Jepson and Jacob, 2007) and a Local Fishery Stock Status Index (LFSSI) (Jacob and Jepson, 2009). Cutter et al. (2010) created a related index of social vulnerability to coastal hazards that connects to geographic place at the county level. While that index has proved beneficial in relating exposure to natural hazards to geographic locale, it does not meet the requirements of National Standard 8 for community-level assessments. Thus, a more focused approach on specific aspects of well-being for fishing communities is warranted. Viable standardized social indicators at the local or community level for U.S fisheries are needed to allow for comparison, both regionally and nationally. The work outlined here is an initial attempt to do so for NOAA Fisheries' Northeast and Southeast Regions.

B. Well-being, Vulnerability and Resilience in Fishing Communities

There are several ways to describe the relationship between the key concepts of well-being, vulnerability, and resilience. Because these concepts have no singular objective meaning but resonate with a wide range of viewpoints, many authors in diverse fields have attempted to define them. For our purpose, it was important to assign objective metrics to the concepts and accept an operational definition of the relationship. We defined the relationship as vulnerability being the immediate pre-disturbance state and resilience as constituting the ability to cope post-disturbance over time. This working definition allows collection of measures of inherent vulnerability and applies them in a model that will allow us to track vulnerability over time and document post-event impacts to evaluate resilience in response to fisheries management actions.

We used the Pollnac et al. (2006[2008]) fisheries SIA conceptual model of well-being as an organizing framework for the development of quantitative measures of vulnerability. We begin with a brief overview of these concepts and their relationship to the social fabric of individuals and communities especially those dependent on fishing.

Well-being

The concept of well-being, well established in the literature as a measure of quality of life (Schneider, 1976; Stiglitz et al. 2009), has been operationalized through both social and economic constructs many times with mixed results (Cobb and Rixford, 1998; Johnston and Carley, 1981). However, considerable research has demonstrated that secondary measures of well-being and its correlates e.g., vulnerability and resilience, can inform us regarding the quality of life of individuals and their communities (Hooghe and Vanhoutte, 2010; Porter, 2011; Smith and Clay, 2010). Nevertheless, developing an adequate and easily replicable quantitative construct of well-being for coastal communities, and more specifically fishing communities, has been difficult (Charles et al., 2009).

The Pollnac et al. (2006[2008]) model (Figure 1) illustrates the relationship between multiple attributes that directly or indirectly influence well-being at individual and community levels. Here we examine the social-community attribute with a direct link to well-being. While we recognize the importance of individual well-being in fisheries management (Marshall and Marshall, 2007) relatively little data exists at this level. In contrast, a considerable amount of secondary data is available at the community level. Further, requirements of both National Standard 8 on communities and the National Environmental Policy Act of 1969 (NEPA; 42 U.S.C. 4332(2)) for attention to cumulative impacts at multiple levels, including communities, necessitate more research on communities than has been available. Given the time constraints that are common in conducting SIAs, and the fact that costs are comparatively small for gathering secondary data on communities, as opposed to the (largely primary) data needed to assess individual well-being, the focus on place based communities allows statistically valid analyses that can be replicated for large numbers of communities and in multiple regions within a relatively short time frame.

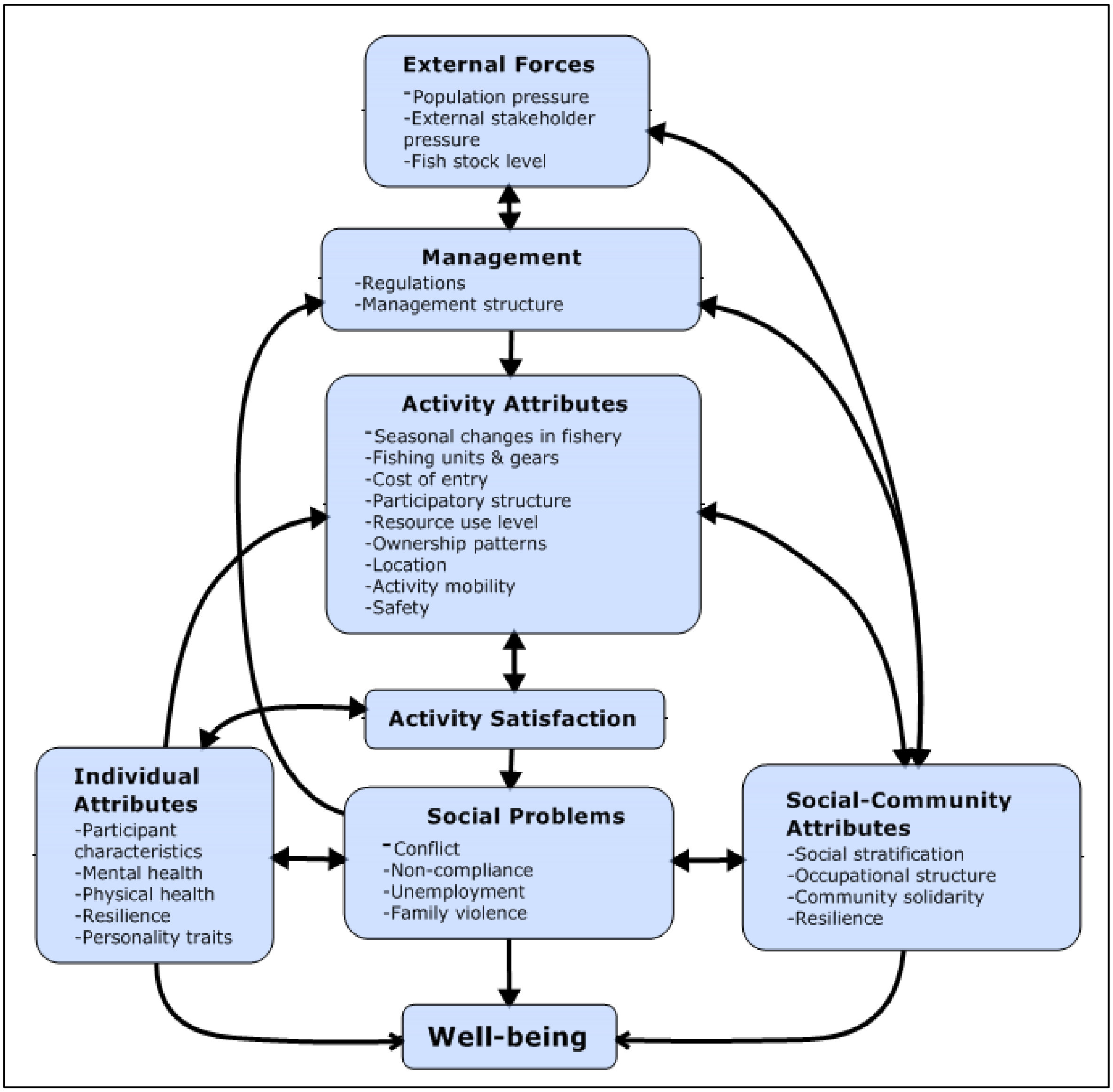

Figure 1. Well-being and Fisheries SIA Conceptual Model.

The concepts of vulnerability and resilience and their relationship to change are important to our understanding of well-being and a community's adaptation to a disruptive event such as a change in fishery management regulations. Research has consistently shown strong correlations between vulnerability and resilience and socioeconomic status (Cutter et al. 2008, 2003; McLeod and Kessler, 1990; Sherrieb et al. 2010). The ability to adapt to change is dependent on the interrelationship between individuals, families, and external conditions that corresponds to the well-being of all (Mederer, 1999). These external conditions include job satisfaction, physical and mental health and functional inter-personal relationships (Pollnac et al. 2006[2008]). Social change can affect all of these, directly or indirectly. Regulation-related changes in work conditions (e.g., ability to choose timing of fishing, level of financial remuneration, time spent at sea) can decrease job satisfaction resulting in negative effects on mental health (e.g., anxiety, low self-esteem, worry, and tension), physical health (e.g., stress-related illness), and impaired personal relationships (e.g., divorce) (Pollnac et al. 2006[2008]; Smith et al., 2003). We apply these concepts to fishing communities using secondary data to derive social indicators that provide some measure of these attributes of well-being.

It is important to note that we are viewing community vulnerability irrespective of it relationship to fishing culture. There are other forces of change-global economy, recession, local and state regulations-that affect communities and the fishing culture. Here we are placing fishing dependency within the context of community vulnerability and resilience understanding that there are feedbacks from one to the other.

Vulnerability and Resilience in Fishing Communities

The use of indicators of vulnerability and resilience in the context of evaluating the response of fishing communities to change is grounded in a broader social scientific effort to gauge the ability of social groups to adapt to change. Social vulnerability and resilience highlight the importance of the interrelationship between both people and the environment (Clay and Olson, 2008). Because the terms have a wide variety of meanings and interpretations, we have developed a practical framework with specific definitions to place the concepts in a model of community response to management actions (Figure 2). This conceptual model allows testing of the social indicators and provides a framework for interpretation of results and development of predictive tools and mitigation measures.

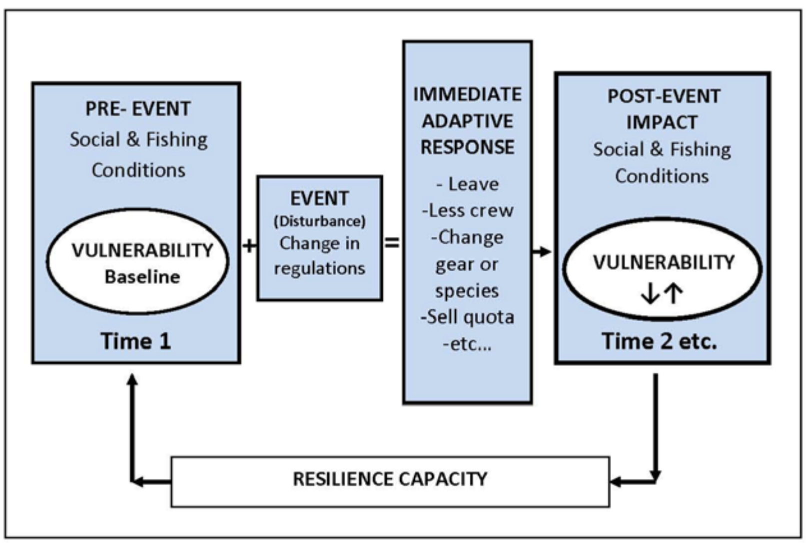

Figure 2. The Vulnerability and Resilience Time Series Model

For example, we might envision a fishing community that is highly dependent upon a particular species of fish "X" and has a robust sense of community spirit as evidenced by participation in community events and institution [Pre-event]. A new stock assessment indicates that overfishing of X is occurring and that X is overfished. The council chooses to reduce the ACL by 100,000 pounds [Event]. This measure causes several vessels to reduce crew. One person sells his vessel and one fish house closes [Immediate adaptive response]. Because of these changes, the community no longer holds fish frys and not enough people are available to work the annual fish festival. This translates into less money raised for lobbying by the local fishing organization. Several families are forced to move from the community and overall social networks are weakened as key people are no longer available for support work and leadership within the community [Post-event Impact]. All of these factors have affected the community's inherent resilience capacity which in turn will feed back into the community's vulnerability or its ability to address future disruptions

While we use a fishing community as an example, it is purely a result of our primary focus being fishery regulatory policy. The social disruption could come from outside of fishing and the social networks related to other aspects of community, not necessarily the fishing economy. We believe this model could apply to any coastal community and accommodate other types of disruptions.

Vulnerability

Vulnerability has multiple definitions, depending on the context such as climate change, natural hazards, poverty and food limitation (Klein and Nicholls,1999; Kelly and Adger, 2000; Barnett, 2003; Moser, 2010;White and Haas, 1975; O'Keefe *et al*., 1976; Cutter, 1996; Oliver-Smith, 1996; Turner *et al*. 2003; Chambers, 1989; Moser, 1998; Watts and Bohle, 1993; Davis 1996). Vulnerability research is often used to identify the characteristics of a population (or community) that influence the social burden of risk and "susceptibility of a given population, system, or place to harm from exposure to the hazard…" (Cutter et al. 2009:2). Further, social vulnerability is centered in both demographic and socioeconomic characteristics of local populations that increase or attenuate the impacts of hazard events (Cutter et al. 2009).

For development of social indicators of vulnerability of fishing communities, we chose to identify pre-event existing social conditions that are likely to affect the impact of disruptive events (Figure 2). The social conditions can lead to adverse or positive responses to these events. Our use of vulnerability includes the following characteristics:

- Pre-event, characteristics of the community that may create or negate the potential for harm
- States of susceptibility to harm, powerlessness, and marginality of physical, natural and social systems
- Patterns of differential access to resources

Resilience

Both the natural and social sciences emphasize that a system can have multiple stable states and that disturbances can force communities to shift from one state to another and still maintain their functional characteristics or be resilient (e.g., Peterson et al., 1998; Folke, 2006). Social scientists usually emphasize a system's ability to cope and adapt to change, but social systems cannot be easily separated from ecological systems. The concept of "social-ecological resilience" attempts to capture this interaction (Walker et al., 2004). What is clear is that the interactions between the human and non-human environment have synergistic aspects and may adapt or transform over time (Folke, 2006).

In developing an operational concept of resilience, we have utilized a set of characteristics that include some aspects of the social-ecological resilience concept but are primarily about social resilience (Pollnac et al., 2006[2008]). We intend to use resilience in the analysis of the response of communities after disruptive events in contrast to vulnerability, which we consider the pre-event condition. In this use, the concept explicitly includes a dimension of time. Our use of resilience includes the following characteristics:

- The ability of a social system to respond to and recover from a disturbance
- The ability of a social system to absorb impacts or cope with stress
- The social system's inherent ability to function well during non-crisis and adapt/be flexible in response to a disturbance event

While we discuss the concept of resilience and believe it is an important aspect within the model of well-being (Figure 1), we do not attempt to operationalize it at the community level. Some of that difficulty resides with what we consider one of the more important components of resilience:social capital. Social capital is often discussed as a key element of resilience, both for individuals and communities, and is often linked to participation in civic groups. While we do not have secondary measures of group participation at the community level at this time, we hope to be able to test this aspect of social capital in the future and further develop a viable measure of resilience.

Social Response of Fishing Communities to External Factors

In order to develop the model of the social response of fishing communities to management actions (Figure 2), it was necessary to place the social indicators of vulnerability described below in relation to concepts of community vulnerability and resilience. Although the relationship between the concepts of vulnerability and resilience is complex and dependent on disciplinary focus and personal preference, it is possible to develop a pragmatic approach to evaluation.

For our model, we have separated the concepts and developed a linear evaluation of pre- and post-event social and fishing conditions (Figure 2). The event in our model is a management action, such as a new regulation of fishing effort. The availability of secondary data means that these events can be in the past, present or future.

The social response model (Figure 2) first considers that coastal communities are comprised of social systems, the built environment, and natural systems. Every community has inherent vulnerability and resilience in each of these systems however our focus is on the measurement of vulnerability. A highly vulnerable community may have multiple social stressors such as significant crime, poverty, and unemployment while a less vulnerable community may have fewer or less significant stressors. A community can also have a degraded housing stock and infrastructure or in contrast, a highly heterogeneous built environment with substantial and recent investment. The natural systems can also be vulnerable to storm surge, temperature change or overharvesting or be relatively invulnerable. Our social indicators focus on the social systems and are measures of the pre-event social and fishing conditions. We consider fishing community vulnerability as the pre-event and post-event existing social and fishing conditions and resilience as the capacity to cope with change over time. In order to understand community resilience, vulnerability must be tracked temporally and in relationship to successive disturbances.

We posit that each management action triggers a variety of responses within the fishing community. When new management regulations are imposed individuals may fish with fewer crew or change target species or gear, or any number of responses – including, potentially, seeking employment outside the fishing industry. We do not attempt to measure these responses at present, but simply assume that they may result in some type of impact on the social indicators. The immediate and cumulative effects of current and past changes combined with the inherent vulnerability (low to high) of the community will determine the extent to which the community can cope with the impact of the regulation. If coping capacity is exceeded, then the capability of the community to respond and recover from the event will be low (less resilient). In contrast, if community coping capacity is not exceeded, then the capability of the community to respond and recover will be greater (more resilient). In this respect, we see the concepts of vulnerability and resilience as operating on separate but related continua[1]. This, we propose, means that changes in vulnerability over time can be an indicator of resilience. Although our present research is a static picture of vulnerability reflected as Time 1 in Figure 2, it is our intention to create future vulnerability measures to compare over time as indicated by Time 2 in the model, thereby giving an indication of resilience until we are able to create viable measures of the concept.

Social Indicators

As we have noted, there has been considerable interest in social indicators through the decades, beginning in the early 1960s with a focus on describing the well-being of society and at times addressing the effectiveness and efficiency of government (Cobb and Rixford, 1998; Fox, 1986; Johnston and Carley, 1981; Porter, 2011; Schneider, 1976). With recent attention focused on ecosystem-based management and ecosystem goods and services, there has been a resurgent interest in indicators, both biological and social (Degnbol 2005; DeYoung et al. 2008; Livingston 2005; MEA 2005a, 2005b). While there has been substantial progress in the creation and implementation of sustainable development indicators for fisheries, as Boyd and Charles (2006) point out, there have been few attempts to develop such measures at the community level. The potential for the development of indicators within an ecosystem-based fishery management regime that includes social and economic variables has been widely promoted (Charles et al. 2009; FAO 1999; Patterson et al. 2010). Only recently have the types of indicators that are easily replicable and applicable to coastal communities appeared in an operationalized form that

[1] This is an adaptation from our previous view that vulnerability and resilience operate on opposite ends of the same continuum (Colburn and Jepson, 2012).

is practical. Cutter's social vulnerability index (SoVI) to coastal hazards at the county level (Cutter et al. 2000; Cutter et al. 2003; Cutter et al., 2010) has been analyzed for sensitivity to scalar change from aggregation at different units of analysis e.g., census tract, county (Schmidtlein et al. 2008) and seems to remain fairly stable. Cox et al. (2006) developed a similar social vulnerability index applied at the block level in the Northeast to assist communities in understanding the vulnerabilities that may affect community action. These examples demonstrate that a comprehensive measure of social vulnerability can be developed and applied at various geographic contexts and for a variety of uses.

In an early attempt to explore social indicators for fishing communities in the U.S., Jepson and Jacob (2007) created an index of vulnerability for Gulf Coast fishing communities that used both census data and a modified shift-share employment analysis. In that assessment, Gulf coast fishing communities received a vulnerability score used to identify those within specific fisheries that may exhibit vulnerabilities to future regulatory change. However, the shift share component was impractical when faced with shortened timeframes for conducting social impact analyses, as it takes considerable time to construct and data are not always available. In the Pacific region, groundfish fishing communities were classified according to their vulnerability using a Shannon Index and other census variables plus a fishing engagement measure all combined into a rank order scale (PFMC, 2006). Jacob and Jepson (2009) further explored an index of reliance on particular fish species for Gulf of Mexico communities that has implications for sustainability. Using landings at the community level and the NOAA Fishery Stock Status Index[2], they developed a measure of a community's reliance upon particular species in comparison to regional landings, allowing evaluation of potential community vulnerabilities related to sustainability that come from reliance on overfished species. Most recently, Jacob et al. (2010, 2012) compiled a series of social indices that gauge a variety of community vulnerability constructs, including reliance upon either commercial or recreational fishing, for a select group of Gulf coast fishing communities. These indices were comprised of U.S. Census, NOAA Fisheries and other secondary data then explored through factor analysis to determine the ability of the index to measure a particular aspect of community well-being.

Although the straightforwardness of Cutter's SoVI (Cutter et al., 2010) is appealing, the concept of well-being is complex. Some aspects of the SoVI for coastal hazards are not essential to assessing vulnerability to regulatory change and its impacts. Furthermore, there are other components of social vulnerability for coastal communities that would be difficult to deduce from a coastal hazards SoVI. A single vulnerability index may not be discrete enough to measure how each component expresses the multiple differing vulnerabilities a community may have. Therefore, we have chosen to divide social vulnerability into several different components by creating individual indices that contribute to the larger concept of well-being while each smaller constituent component provides a more refined portrayal of each factor, similar to Jacob et al. (2010, 2012).

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[2] NMFS measures the sustainability of our Nation's fisheries through the Fish Stock Sustainability Index (FSSI). The FSSI measures the performance of 230 key stocks and was calculated by assigning a score for each fish stock or complex based on a set of rules concerning overfishing and other stock status measures. For a detailed explanation, see: http://www.nmfs.noaa.gov/sfa/statusoffisheries/SOSmain.htm.

VI. Methods

This project was developed in two phases (Figure 3). Prior to undertaking our research, a group of regional fisheries experts and social scientists familiar with social indicators and fishing communities were convened in 2010 to assist in the development of an approach to create measures of fishing community well-being. A second workshop held in 2011, shortly after the initial development of indicators, was to review and suggest revisions to the indicators.

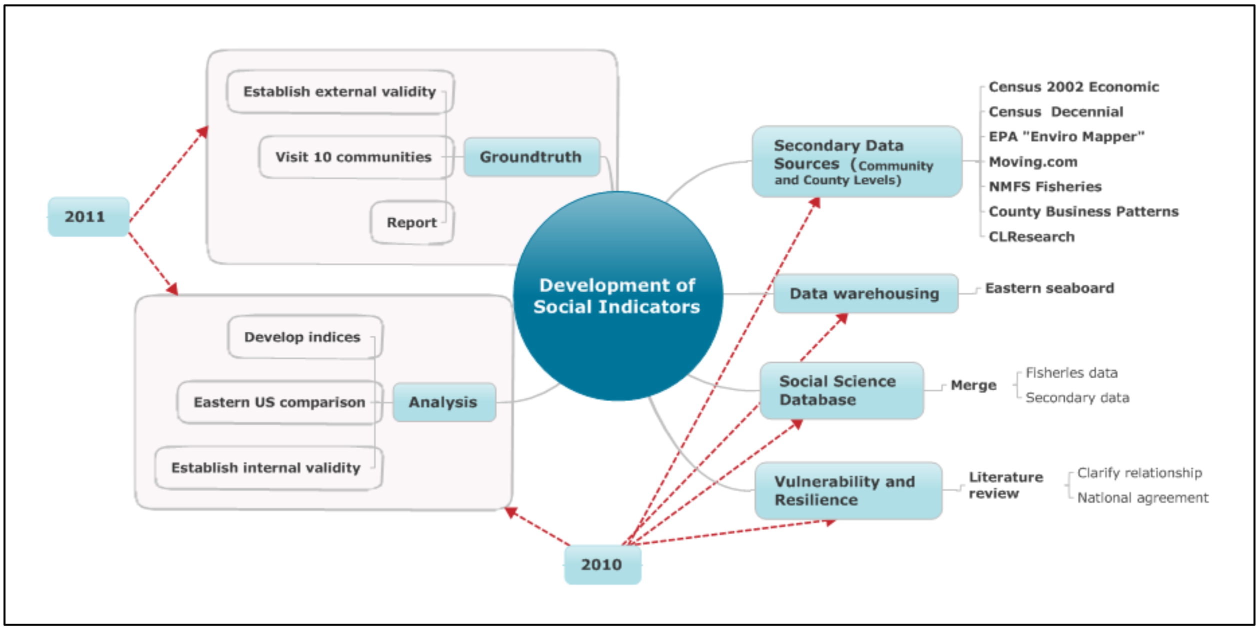

Figure 3. Model for Development of Social Indicators for Fishing Communities.

A. Workshops

Miami Workshop

The first three-day workshop held in May 2010 at the Southeast Fisheries Science Center (SEFSC) in Miami, Florida identified key variables for constructing social indices of fishing community vulnerability. Attendees included social scientists from NMFS Headquarters and the Northwest, Northeast, Pacific Islands and Southeast Fisheries Science Centers, and the Southeast Regional Office. Several individuals outside of NOAA with expertise in the construction of these indices also attended and provided advice and potential data warehousing solutions.

The purpose of the workshop was to identify needed data and data sources, and a methodology for assembly of the social indicators. A review of social indicators from Jacob et al. (2010) and work on gentrification in the Northeast were presented to assist in selecting pertinent data for constructing social indicators that would be both meaningful and adequate for social impact assessment. In addition, participants suggested ways to warehouse collected and analyzed data and provided an overview of needed data types.

Silver Spring Workshop

A second workshop held in September 2011 in Silver Spring, Maryland, reviewed the set of indicators developed and applied to coastal communities along the Eastern and Gulf coasts since the previous workshop[3]. We presented a group of 12 community vulnerability indices that measured aspects such as labor force, housing characteristics, poverty, gentrification, and fishing dependence. Participants reviewed and discussed the concepts of resilience and vulnerability at length and reviewed each index and recommended revisions. In addition, the discussions included new indices that might be developed and other variables adding to or replacing current variables in the indices.

B. Analytical Approach

The approach selected for constructing our indices of community vulnerability closely follows that developed by Jacob et al. (2010, 2012). Building on work by Cutter et al. (2003) and Jepson and Jacob (2007), this approach utilizes several indices to examine different aspects of social vulnerability and over time resilience for each location, concentrating on those relevant to the coastal economy and fishing communities.

Data Collection

We collected data from both public and private sources for over 2,900 communities in coastal counties in 19 states from Maine to Texas. Estimate data at the place level had recently become available through the Census Bureau's American Community Survey (ACS 2006-2009). Census data collected on line through the American Factfinder constituted the bulk of the community demographic component. Community data for crime and hazardous weather variables collected from nongovernmental websites augmented our demographic profile. We collected fisheries data, such as number of permits and volume and value of landings, from both the Northeast and Southeast Science Centers. The entire list of 120 variables selected for the analysis is available in Appendix 2.

We assembled the data for every Census Designated Place (CDP) from a set of predetermined coastal counties along the Eastern and Gulf coasts. The criterion for coastal county designation was that it has some connection with the ocean, through a coastline, river, bay or estuary. This criterion was chosen as we envisioned communities within these counties to have comparable economies and experiencing similar vulnerabilities that come from having ocean front property or beaches, inlets and bays with access to the ocean and many of the amenities that make coastal living such a desirable destination to so many. Communities were not chosen based upon their

[3] http://www.st.nmfs.noaa.gov/st5/social/workshop.html

fishing activity, but once selected fishing activity was placed within the context of that community. Thus, communities included in this analysis are coastal communities with some NS8 fishing communities included. Once we had verified that datasets for both the Northeast and Southeast were complete and verified that all variables and calculations corresponded, we began to factor analyze our data.

Factor Analysis

Factor analysis is a data reduction technique that allows for the construction of indices that represent the latent structure of a conceptual variable. Latent concepts are unobservable, but variables taken together can represent the concept, much as the concept of inflation is measured by the consumer price index. Here, our constructs relate to several concepts of well-being and fishing activity and correspond to vulnerability to social change at the community level.

We initiated our index construction using the variables originally chosen by Jacob et al. (2010, 2012). The factor analysis process consisted of a principal component analysis with a varimax rotation. Using a varimax rotation allows one to determine which variables are loading the highest onto the factor and would more likely result in a one-factor solution if included when a single factor is not achieved. When we were unable to achieve a one-factor solution with a particular set of variables for an index, we substituted comparable variables that had high factor loadings within the overall principal component analysis until we found a satisfactory one-factor solution. We also used substitution of the mean for missing data to ensure each community would receive a scale score and also because we had relatively few missing data.

At the outset, we created indices for the Southeast Region and then attempted to duplicate them for the Northeast Region. Where regional indices differed with regard to multiple factors or differential availability of specific variables, we again chose comparable substitute variables until we obtained corresponding results, meaning each index contained the same variables and a one-factor solution. Once we achieved agreement on all indices, we combined data from both regions and repeated the factor analyses. We retained an index if it remained a single factor solution and met all criteria thresholds and significance levels. The criteria of significance for all indices included total variance explained above .450. Although this may be low, for exploratory analysis and selecting a single factor solution, this criterion should be acceptable as we are looking for as few factors as possible. The Kaiser-Meyer-Olkin measure of sampling adequacy above .500 was chosen to compare the magnitudes of the observed correlation coefficients in relation to the magnitudes of the partial correlation coefficients, higher values are better. Factor loadings were all to be above .350 and Bartlett's test of sphericity significance above .05 was adopted to test the hypothesis that the correlation matrix is an identity matrix. And finally, Armour's Theta reliability

was used as it does not assume that all items are weighted equally, only coefficients above .500 were retained. In the final analysis, we created 14 original indices used in conjunction with a Shannon index of occupational diversity. The results follow with a detailed description of each index.

VII. Results

A. The Indices

We placed the indices under one of three categories within the larger context of vulnerability. The three main categories are social, gentrification, and fishing dependence vulnerability. While gentrification is both social and economic in its effect, the process itself has special significance as it creates different vulnerabilities and is thought to deserve consideration as a discrete process from other social and economic vulnerabilities (GSAFFI, 2010; Colburn and Jepson, 2012). For each category, we present the index, the variables included, the factor loadings for each variable, and the percent of total variance explained. For the labor force structure and housing characteristics indices, it was necessary to reverse the scores so that all indices had a common directional tendency with regard to vulnerability. For instance, a high score on the original labor force index means a strong labor force with more overall participation including more females and fewer self employed. Reversing the scores on this index means that low scores are now high and higher scores are associated with greater vulnerability. These indices are marked with an asterisk (see Table 1d and 1c).

Appendix 1 includes a table for each index that displays factor scores[4] for a select group of communities. The value of each variable within an index for a particular community is included in the table along with the corresponding factor loading which represent each variable's contribution to the index. The index factor scores in the last column represent each community's rank within each index. Each index table contains the variance explained, highest eigenvalue and theta reliability score. These communities also appear in the radar graphs below.

We selected communities for this discussion using a methodology for classifying coastal communities for sampling purposes (Smith et al. 2011). All communities showed some level of involvement in either commercial or recreational fishing. Using a community's factor scores for each discrete index, a K-means cluster analysis was used to create a taxonomy of fishing communities (Pollnac 2012). This resulted in a typology of 35 communities clusters. Each cluster of communities has a unique set of shared characteristics for each index included in the analysis. For example, scores for one cluster may indicate a high degree of involvement in commercial fishing and be characterized by a strong labor force and low risk of gentrification while another cluster may show the opposite. This method made it possible to select communities with a wide range of involvement in commercial and/or recreational fishing and exhibiting varying degrees of social vulnerability.

[4] The factor scores for each index and community are a product of the factor analysis process. Within SPSS, these factor scores are saved and become an additional variable within the dataset for each community and are labeled as such.

Social Vulnerability

The six indices created under the larger descriptor of social vulnerability are presented in Table 1. Each of these indices corresponds to one of the many components identified throughout the literature as corresponding to social vulnerabilities that may affect communities. Variables chosen for each index have appeared in existing indices (Cutter et al., 2010; Jacob et al., 2012) or are recognized as an important marker of that particular vulnerability (Table 1).

Personal disruptions (Table 1.a.) includes variables associated with the kinds of changes and circumstances that might affect a person's ability to find work, propensity to be affected by crime, exposure to poverty, or personal circumstances affecting family life or educational level. Therefore, the community as a whole will exhibit vulnerabilities when these factors are combined. Higher factor scores equal higher levels of vulnerability for this index.

Table 1. Social Vulnerability Indices.

Index Variable	Factor Loadings	Percentage Variance Explained
a. Personal Disruption Index		
Percent unemployed	**0.628**	
Crime index	**0.477**	
Percent with no diploma	**0.786**	**45.00**
Percent in poverty	**0.811**	
Percent females separated	**0.600**	
b. Population Composition Index		
Percent white alone	**-0.898**	
Percent female single headed households	**0.719**	
Percent population age 0-5	**0.675**	**58.12**
Percent that speak English less than well	**0.739**	
c. Poverty Index		
Percent receiving assistance	**0.544**	
Percent of families below poverty level	**0.915**	
Percent over 65 in poverty	**0.716**	**59.72**
Percent under 18 in poverty	**0.862**	
d. Labor Force Structure Index*		
Percent females employed	**0.905**	
Percent population in the labor force	**0.951**	
Percent of class of worker self employed	**-0.355**	**65.25**
Percent population receiving social security	**-0.872**	
e. Housing Characteristics Index*		
Median rent in dollars	**0.814**	
Median mortgage in dollars	**0.882**	
Median number of rooms	**0.751**	**60.60**
Percent mobile homes	**-0.648**	
f. Housing Disruptions Index		
Percent change in mortgage	**0.801**	
Percent change in home values	**0.810**	**53.00**
Percent of owners monthly costs 35% of income	**0.540**	

* Scores reversed to ensure directional continuity with other scales.

Population composition (Table 1.b.) is comprised of variables that correspond to the demographic makeup of the population. These variables, which measure the percentage of minorities, the percent of young children and female-headed households and the ability to speak English well are all common components identified as indicators of socially vulnerable populations. Higher factor scores equal higher levels of vulnerability for this index.

Our poverty index (Table 1.c.) contains several different poverty variables that cover all facets of the concept including the elderly, young and families in poverty along with the general percent of population receiving assistance. Higher factor scores equal higher levels of vulnerability for this index, as well.

Labor force structure (Table 1.d.) includes variables that are indicative of the types of engagement within the labor force by examining the percent of the total population and the number of females that are in the labor force, the percent of those who may be retired and those who are self-employed. These variables combined lend themselves to a characterization that provides an indication of the strength and stability of the labor force. Factor scores were reversed so higher factor scores would equal higher levels of vulnerability for this index.

The housing characteristics index (Table 1.e.) has several variables that relate to the character of housing available within a community by measuring the average rent and mortgages and median number of rooms. The percentage of mobile homes within a community adds to that characterization as an indication of either temporary or seasonal housing and an indication of socio-economic status and has a negative loading in contrast to the other variables. Again for this index, factor scores were reversed so higher factor scores would equal higher levels of vulnerability.

For our measure of housing disruption (Table 1.f.), we settled on a three-item index. It includes the changes in mortgages and home values from 2000 to 2010 as an indication of fluctuating housing markets, along with the percent of owner monthly costs that may indicate a higher number of owners struggling as their mortgages consume a large part of their income. This index provides an overall depiction of disruptions in the housing market that may be due to changing home values. Higher factor scores equal higher levels of vulnerability for this index.

To demonstrate how one might utilize these indices, we plotted the individual index factor scores for a set of communities onto radar graphs to help visualize the interrelatedness of each index and to compare communities. The selected set of communities is the same as that in tables presented in Appendix 1. There you can view each community's factor score for a particular index and see a map of the entire index plotted by factor scores standard deviation.

A black circular line on each index chart below represents our threshold of 1 standard deviation above the mean. We suggest that scores beyond this threshold would indicate a community is experiencing vulnerabilities regarding a particular index or set of indices. We chose one standard deviation as it has been used in previous research. Norman et al. (2007) used one standard deviation as their threshold for profiling fishing communities analyzed through Data Envelopment Analysis. Cutter (2003) also used a range from -1 to 1 standard deviations with ½ standard deviation increments with counties where scores were greater than 1 standard deviation being the most vulnerable. One standard deviation may be conservative and a lower threshold might be more appropriate, however groundtruthing of this methodology will inform our understanding of the appropriateness of this threshold and whether revision is necessary.

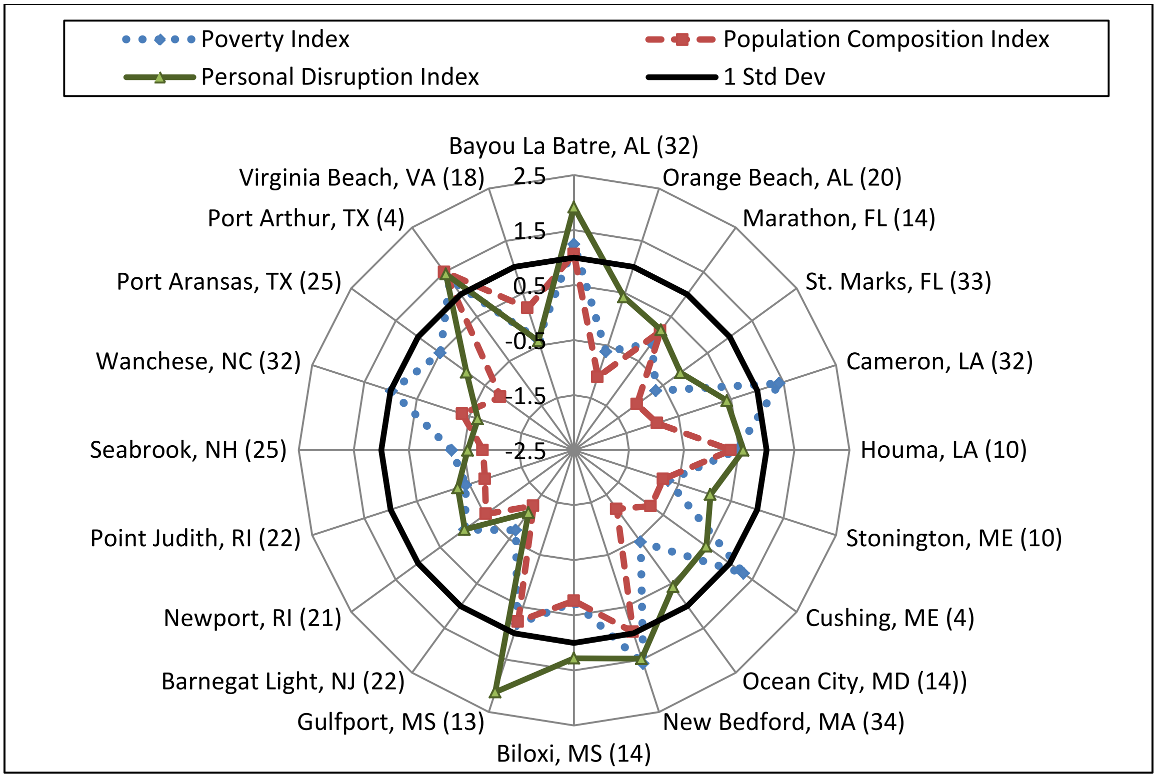

Figure 3. Social Vulnerability Indices by Community.

Several communities demonstrate vulnerabilities with regard to the three indices of social vulnerability plotted in Figure 3. The communities of Bayou La Batre, AL, New Bedford, MA, and Port Arthur, TX exceed the threshold of one standard deviation on all three indices. The community of Gulfport, MS exceeds the threshold for personal disruption and is close to the threshold on the other two indices. We suggest that these communities are exhibiting social vulnerability as demonstrated by their factor scores and the directionality of each indicator.

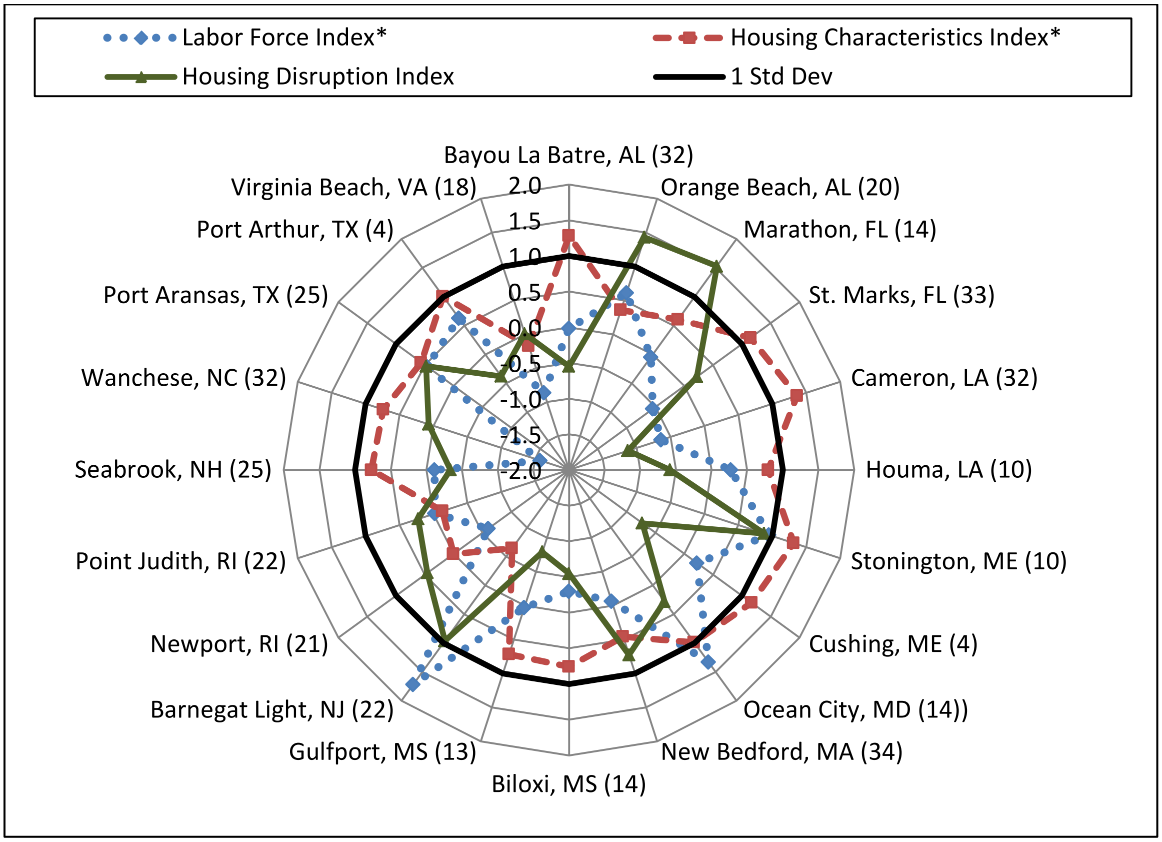

Figure 4. Social Vulnerability Indices by Community (cont).

In Figure 4, we plotted the additional three social vulnerability indices with no community exceeding the threshold for all three indices. However, Ocean City MD, Stonington ME, and Barnegat Light, NJ all have two indices at or exceeding the threshold. Again, we would suggest that these communities are exhibiting vulnerabilities or have the potential to become vulnerable because of these social factors, especially those communities that are also exhibiting scores beyond the threshold in Figure 3 have compounded vulnerabilities.

Gentrification Indices of Vulnerability

The three components of gentrification we created are retiree migration, urban sprawl and natural amenities (see Table 2). We selected the variables for each index based on previous research and literature on gentrification trends and the potential threat to fishing communities (GSAFFI, 2010; Colburn and Jepson, 2012; Gale, 1991; Hall-Arber et al. 2001; Coastal Enterprises Inc. 2002). It is has been frequently noted that with the influx of retirees into coastal communities, who are often from much different places (the Midwest or an inland part of a coastal state), there comes a change in social networks, local power structures, and property tax base (Gale, 1991; Lamarque, 2009). These impacts often appear through changes in population growth, an increase in the cost of living and a rise in home values, all variables included in our urban sprawl index. Furthermore, much of the in-migration to coastal communities is driven by proximity to natural amenities. Those amenities are commonly associated with a coastal economy, often based upon tourism and recreation, which we measure through vacant homes and rentals along with a measure of water area and boating infrastructure.

Table 2. Gentrification Vulnerability Indices

Index Variable	Factor Loadings	Percentage Variance Explained
Retiree Migration Index		
Households with one or more over 65	**0.950**	
Percent population receiving social security	**0.951**	
Percent receiving retirement income	**0.766**	**78.59**
Percent in labor force	**-0.866**	
Urban Sprawl Index		
Population Density	**0.387**	
Nearest city w/50k population in miles	**-0.589**	
Cost of living index	**0.894**	**49.10**
Median home value	**0.819**	
Natural Amenities Index		
Rental vacancy rate	**0.770**	
Percent homes vacant	**0.824**	
Boat launches per 1,000 persons	**0.605**	**48.80**
Percent water cover	**0.493**	

For our measures of coastal gentrification in Figure 5, we plotted the three indices from Table 2. While only one community, Barnegat Light, NJ, has all three gentrification indices exceeding the threshold of one standard deviation, we would again suggest that for those communities where all three index scores are directionally toward the threshold or two of the indices exceed the threshold, gentrification vulnerabilities are present or developing. Due to regional variations in population density, it should be noted that urban sprawl is much less important for communities in the Southeast than in the Northeast.

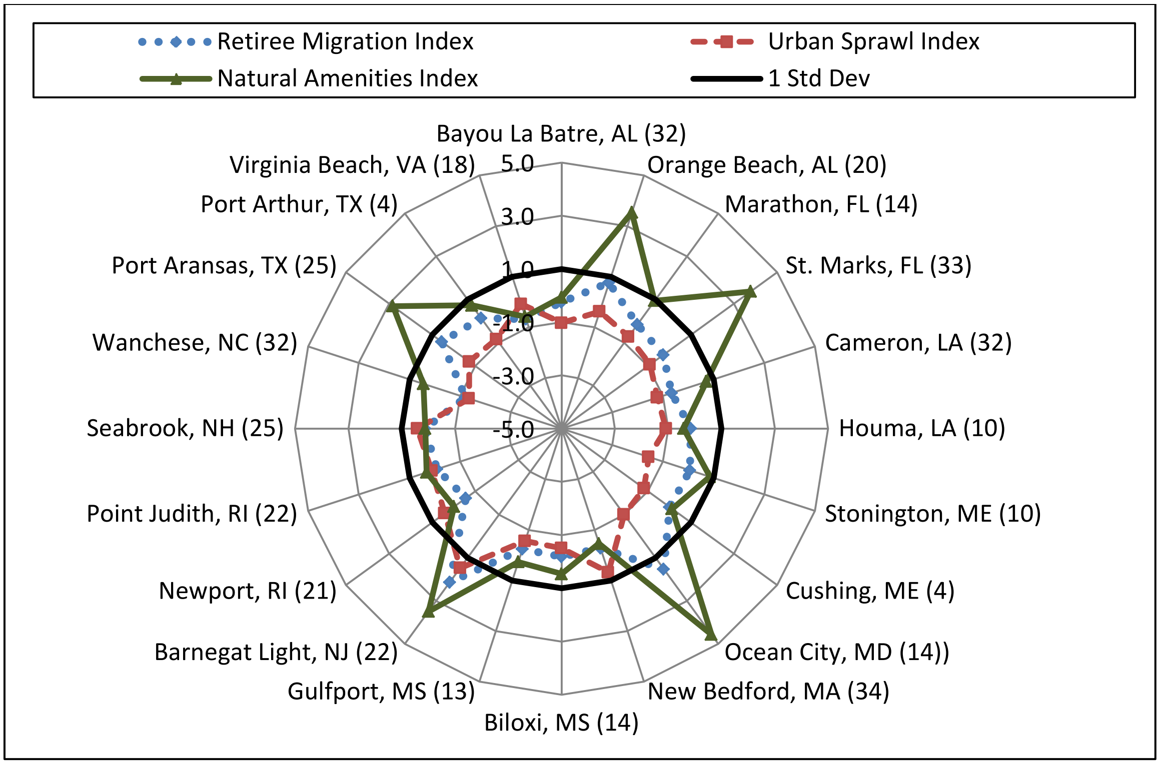

Figure 5. Gentrification Vulnerability Indices by Community.

Fishing Engagement and Reliance

To create indicators of community dependence on fishing, we developed a range of complementary measures related to fishing activity that cover both engagement and reliance. Commercial and recreational fishing engagement are absolute measures of fishing activity as measured by the absolute numbers of that activity. For commercial fishing we used permits, pounds and value of landings and number of dealers for commercial fishing. For receational engagement we used estimated fishing trips from the Marine Recreational Information Program (MRIP) site survey for recreational fishing. The MRIP site survey assigns a community name associated with each site location selected for interviewing. We used estimates of fishing pressure-fishing trips) by fishing mode for each site. The mode refers to the type of recreational fishing that is being engaged, whether from a private boat, charter boat, or shore fishing. We summed the site estimates for each mode by community identified on the survey. This summation of each mode was our measure of recreational fishing engagement by community.

The commercial and recreational reliance indices are relative measures consisting of similar variables related to commercial or recreational fishing activity (Table 3). For commercial reliance we used value of landings per capita; number of commercial permits per capita; number of dealers per capita and percentage employed in agriculture, forestry and fishing. For recreatoinal fishing reliance we used the same summation of mode fishing pressure divided by populaiton. Each variable is divided by the population and is either multiplied by a constant, e.g., 1,000 or used as is and reflects the amount of fishing activity in relation to the size of the population.

Table 3. Fishing Engagement and Reliance Indices

Index Variable	Factor Loadings	Percentage Variance Explained
Recreational Fishing Reliance Index		
Recreational fishing mode charter per capita	**0.352**	
Recreational fishing mode private per capita	**0.917**	**58.97**
Recreational fishing mode shore per capita	**0.897**	
Recreational Fishing Engagement Index		
Recreational Charter Fishing Pressure	**0.352**	
Recreational Private Fishing Pressure	**0.815**	**63.02**
Recreational Shore Fishing Pressure	**0.761**	
Commercial Fishing Reliance Index		
Value of landings per capita	**0.833**	
Number of commercial fishing permits per capita	**0.686**	
Dealers with landings per capita	**0.592**	**50.30**
Percent in agriculture, forestry and fishing	**0.705**	
Commercial Fishing Engagement Index		
Value of landings	**0.906**	
Number of commercial fishing permits	**0.862**	
Dealers with Landings	**0.580**	**57.57**
Pounds of Landings	**0.635**	

Our two measures of commercial fishing activity for the select group of communities are displayed in Figure 6. These two indices are closely related, but a few communities stand out. New Bedford, MA has by far the highest engagement score for a commercial fishing community. In fact, we truncated the value for the purposes of comparison of scale on this graph. With its high value of landings (highest in the nation), the community is highly engaged, but not highly reliant upon fisheries. While most communities had values beyond the threshold for both indices, a few seem to stand out with higher factor scores on reliance (see Appendix A - Table 12). Stonington, ME; Barnegat Light, NJ; Point Judith, RI; Bayou La Batre, AL; Cameron, LA; Wanchese, NC; St. Marks, FL and Port Arthur; TX have index scores that exceed the threshold by a much larger margin than other communities do. These communities are likely to be more dependent upon commercial fishing as we see both high engagement and reliance.

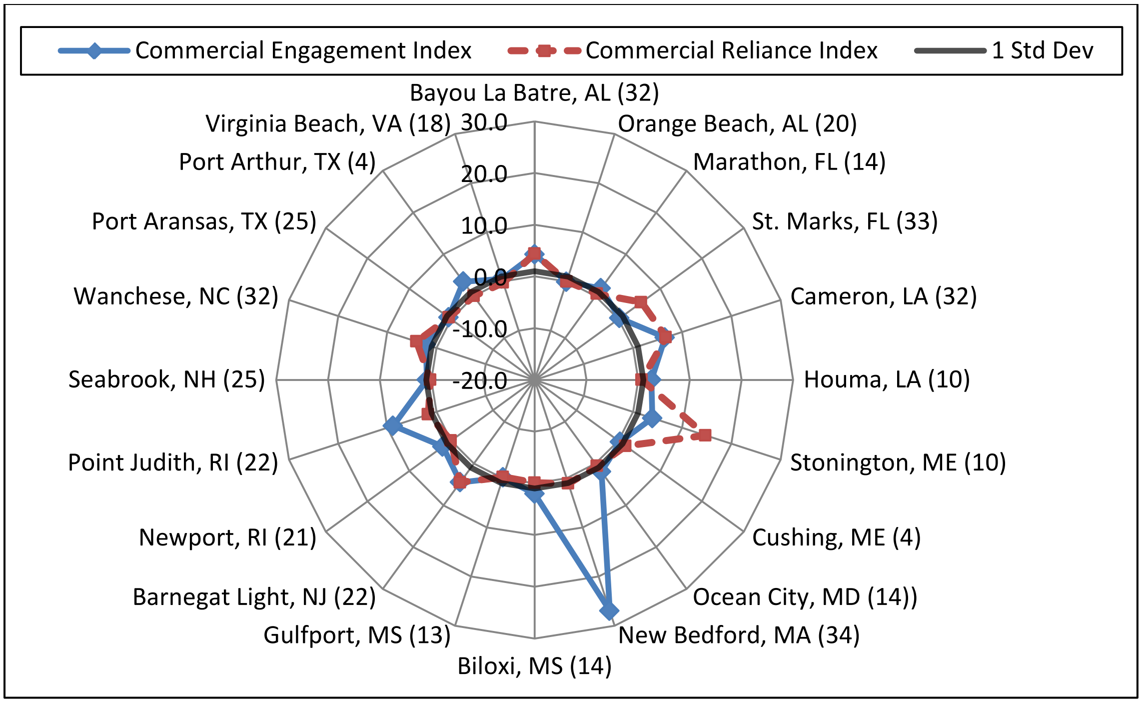

Figure 6. Commercial Fishing Engagement and Reliance Indices by Community.

In Figure 7 below, we have plotted our measures for recreational fishing reliance and engagement for these same communities. Several communities show a similar dependence upon this type of fishing economy with its many components. Our measures of recreational reliance and engagement are closely aligned, although some communities do exhibit distinct differences. The communities of Virginia Beach, VA; Orange Beach, AL; Marathon, FL; St. Marks, FL; Ocean City, MD; Biloxi, MS; Gulfport, MS; Barnegat Light, NJ; Newport, RI and Point Judith, RI all exceed the threshold for both recreational engagement and reliance, which would suggest these communities have an economy that is at least somewhat dependent on recreational fishing.

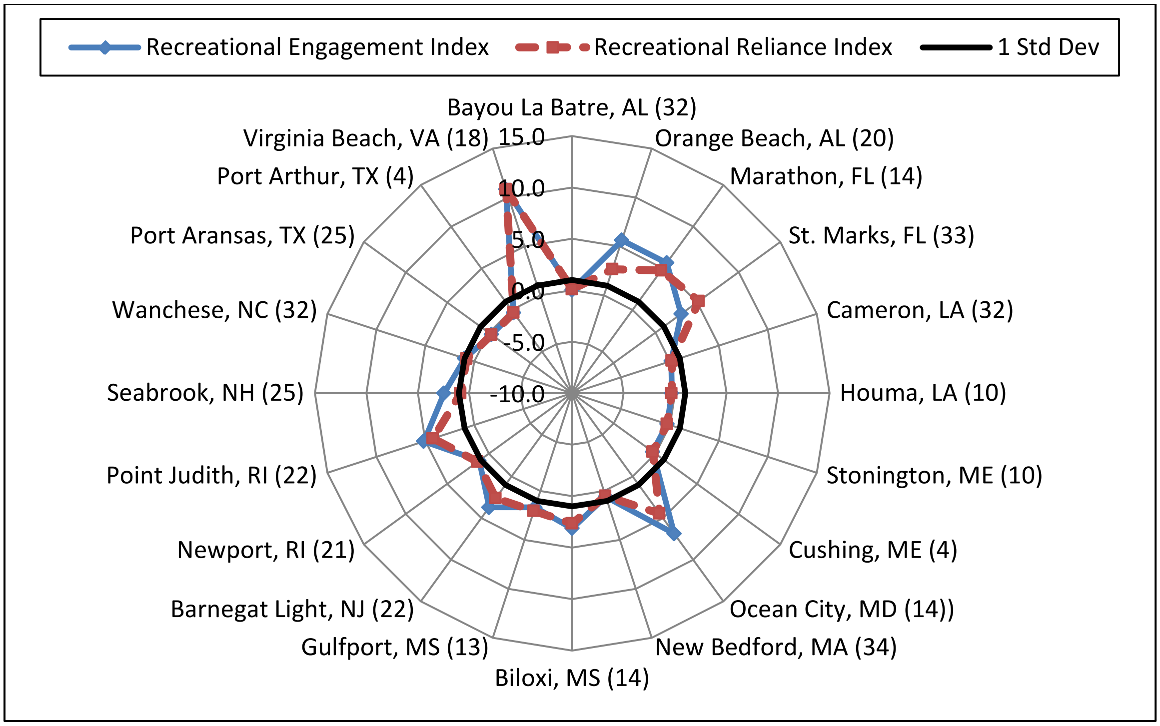

Figure 7. Recreational Fishing Engagement and Reliance Indices by Community.

Finally, we calculated a Shannon Diversity Index (Figure 8) to provide a measure of the occupational diversity within a community (See Appendix 3 for calculation information). The Shannon Index is commonly used to calculate biodiversity (though was originally created to measure linguistic diversity), but has been adapted by many other disciplines. We used the six occupation categories within the Census ACS dataset for this calculation.

The closer a community is to zero, the less occupational diversity it exhibits. The index mean for all communities, represented by the black line in Figure 8, shows several communities scoring below the mean[5]. Gulfport and Biloxi, MS, however, exhibit the least amount of diversity with index scores of 0.66 and 0.68 respectively. This indicator, in combination with other measures provides a sense of those communities that may be more reliant upon one occupation. If that occupation were fishing, as demonstrated through other indices such as the commercial and recreational reliance and engagement indices, then we would conclude that this particular community might be vulnerable to fishery management actions where job losses are anticipated impacts. With little occupational diversity, community members may be forced to look for work elsewhere. However, because occupations related to fishing show up in several different census occupation categories, one could wrongly conclude that occupational diversity is present when there is still an over-reliance upon fishing related employment. Thus, care must be taken in evaluation of an index alone; more in-depth study may be necessary to clarify these results.

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[5] Here is the mean is used rather than one standard deviation. This index score does not correspond to the other indices and the mean is presented only for demonstration purposes. The key is how close to zero is the index score.

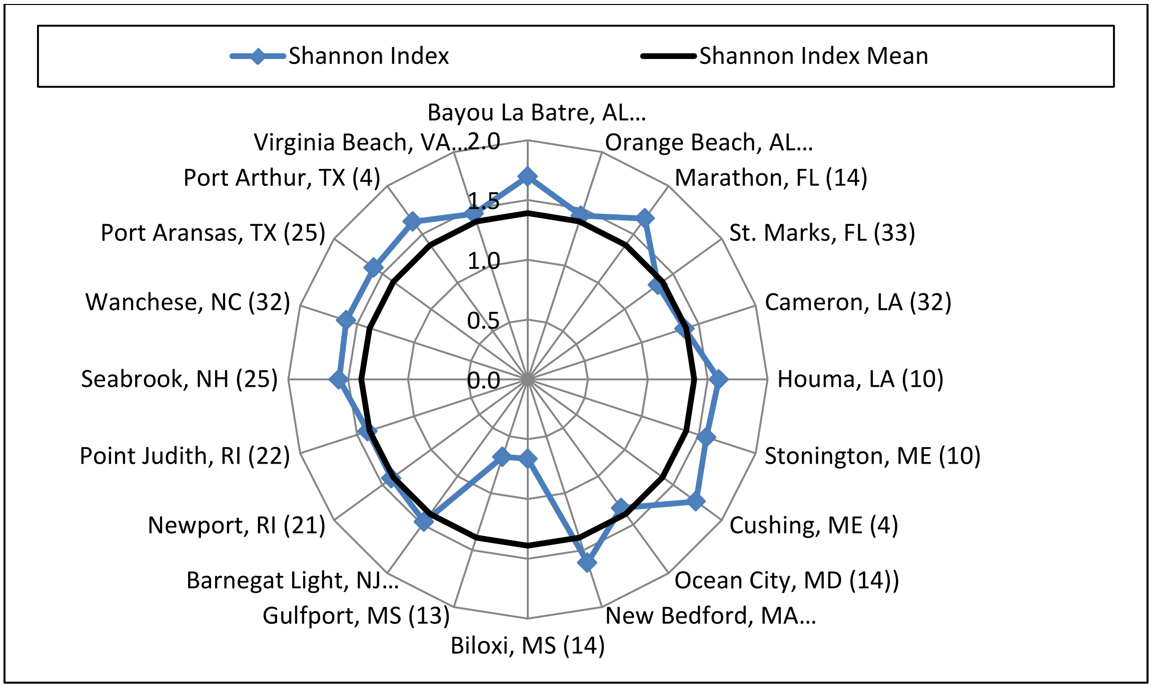

Figure 8. Shannon Index of Occupational Diversity and Mean by Community.

B. Summary Tables

To provide a summary of the data in the graphs above, the results are presented in three different tables below using a dichotomous scale of 1 and 0 for a selected group of indices. A community receives a 1 if each factor score for a particular index is at or over one standard deviation above the mean and 0 if below.

Table 4. Sum of Social Vulnerability Indices Dichotomous Scale.

Community	Poverty	Population Composition	Personal Disruption	Housing Disruption	Housing Characteristics	Labor Force Characteristics	Social Vulnerability Sum
Port Arthur, TX	1	1	1	0	1	0	4
Bayou La Batre, AL	1	1	1	0	1	0	4
New Bedford, MA	1	1	1	0	0	0	3
Cushing, ME	1	0	0	0	1	0	2
Stonington, ME	0	0	0	0	1	1	2
Ocean City, MD	0	0	0	0	1	1	2
Cameron, LA	1	0	0	0	1	0	2
Gulfport, MS	0	0	1	0	0	0	1
Marathon, FL	0	0	0	1	0	0	1
Orange Beach AL	0	0	0	1	0	0	1
Biloxi, MS	0	0	1	0	0	0	1
Barnegat Light, NJ	0	0	0	0	0	1	1
Wanchese, NC	1	0	0	0	0	0	1
St. Marks, FL	0	0	0	0	1	0	1
Houma, LA	0	0	0	0	0	0	0
Virginia Beach, VA	0	0	0	0	0	0	0
Point Judith, RI	0	0	0	0	0	0	0
Newport, RI	0	0	0	0	0	0	0
Port Aransas, TX	0	0	0	0	0	0	0
Seabrook, NH	0	0	0	0	0	0	0

Scores for all six indices were summed for each community with above the threshold of one standard deviation for at least three of the indices highlighted in Table 4; communities where at least 2 of the indices are above the threshold for individual fishing sectors and 3 and above for the fishing sector total are highlighted in Tables 5 and 6.

Port Arthur, TX and Bayou La Batre, AL stand out as exhibiting vulnerabilities to social disruptions as they score above the threshold on four indices. We assume that these two communities may have difficulties in rebounding from any disruption to the local economy because of fishery management regulation. Therefore, within any social impact assessment these communities should be highlighted as vulnerable. Communities scoring above the threshold for three of the indices, e.g., New Bedford, MA, might also be considered vulnerable.

Table 5. Sum of Gentrification Vulnerability Indices Dichotomous Scale.

Community	Retiree Migration	Urban Sprawl	Natural Amenities	Gentrification Sum
Barnegat Light, NJ (22)	1	1	1	3
Ocean City, MD (14))	1	0	1	2
Orange Beach, AL (20)	0	0	1	1
St. Marks, FL (33)	0	0	1	1
Stonington, ME (10)	0	0	0	1
Biloxi, MS (14)	0	0	1	1
Point Judith, RI (22)	0	0	1	1
Port Aransas, TX (25)	0	0	1	1
Bayou La Batre, AL (32)	0	0	0	0
Marathon, FL (14)	0	0	0	0
Cameron, LA (32)	0	0	0	0
Houma, LA (10)	0	0	0	0
Cushing, ME (4)	0	0	0	0
New Bedford, MA (34)	0	0	0	0
Gulfport, MS (13)	0	0	0	0
Newport, RI (21)	0	0	0	0
Seabrook, NH (25)	0	0	0	0
Wanchese, NC (32)	0	0	0	0
Port Arthur, TX (4)	0	0	0	0
Virginia Beach, VA (18)	0	0	0	0

The summation of our gentrification measure is found in Table 5. Both Barnegat Light, NJ and Ocean City, MD exceed the threshold on at least two of the three gentrification indices. We would expect these communities to be vulnerable to gentrification. This predisposition toward gentrification can be problematic for those employed in fishing as it may signal a transition toward an economy no longer based on fishing or water related occupations.

Our summary for fishing dependence (Table 6) has summations of both commercial and recreational fishing and a total fishing summary. Seven communities score above our threshold on both commercial engagement and reliance. We would expect these communities to be more dependent on commercial fishing than the others. Similarly, the ten communities that exceed the threshold for the two measures of recreational fishing activity would be expected to demonstrate some dependence upon recreational fishing. Finally, eight communities in Table 6 exceed the threshold on three or more of the fishing indices as reflected in the Total Fishing Sum. These communities show an overall dependence upon a fishing economy in general and could be affected by management action on either the commercial or the recreational sector.

Table 6. Sum of Fishing Dependence Indices: Commercial and Recreational Fishing Engagement and Reliance Dichotomous Scales.

Community	Commercial Engagement	Commercial Reliance	Commercial Sum	Recreational Engagement	Recreational Reliance	Recreational Sum	Total Fishing Sum
Barnegat Light, NJ (22)	1	1	2	1	1	2	4
Point Judith, RI (22)	1	1	2	1	1	2	4
Marathon, FL (14)	1	0	1	1	1	2	3
St. Marks, FL (33)	0	1	1	1	1	2	3
Ocean City, MD (14))	1	0	1	1	1	2	3
Biloxi, MS (14)	1	0	1	1	1	2	3
Newport, RI (21)	1	0	1	1	1	2	3
Wanchese, NC (32)	1	1	2	1	0	1	3
Bayou La Batre, AL (32)	1	1	2	0	0	0	2
Orange Beach, AL (20)	0	0	0	1	1	2	2
Cameron, LA (32)	1	1	2	0	0	0	2
Stonington, ME (10)	1	1	2	0	0	0	2
New Bedford, MA (34)	1	1	2	0	0	0	2
Gulfport, MS (13)	0	0	0	1	1	2	2
Virginia Beach, VA (18)	0	0	0	1	1	2	2
Houma, LA (10)	1	0	1	0	0	0	1
Cushing, ME (4)	0	1	1	0	0	0	1
Seabrook, NH (25)	0	0	0	1	0	1	1
Port Arthur, TX (4)	1	0	1	0	0	0	1
Port Aransas, TX (25)	0	0	0	0	0	0	0

The summary tables are another way to demonstrate overall fishing dependence as reflected in both community engagement and reliance. The community comparison is one way to use these indices in a social impact assessment to identify those places where vulnerabilities might exist for a specific management action. It may also be possible to measure fishing dependence in relation to species or species groups. A more detailed description of community involvement in a particular fishery and possible effects from management actions that is placed into the context of these vulnerabilities provides a more empirical measure of vulnerability and, over time, resilience that can be assembled in a relatively short amount of time. These indicators contribute to improving social impact assessment of fishery management actions, especially when combined with other types of quantitative and qualitative analyses.

VIII. Discussion

There are a few limitations to this approach, the first being the relative availability of data for different geographic units of analysis. Most of the data collected here are at the Census Designated Place (CDP) level. These data are not always available for communities that have fishing related businesses, in that not all of such communities are identified CDPs. Databases built around different levels of geography, like zip codes, census blocks, or Minor Civil Divisions (MCDs), can be created, but do make assembling data for meaningful community descriptions more difficult.

As NMFS began profiling fishing communities it became obvious that decisions had to be made regarding the geographical boundaries for data collection purposes. The decision to use a particular geographic boundary was a regional decision based upon the characteristics surrounding a particular community and its participation within its region's fisheries. In most cases, CDP[6] was chosen to represent community boundaries. Although CDP does not always correspond to an incorporated place, it is used by the Census Bureau for the purposes of data collection and does include incorporated cities, towns and villages. For these analyses, while CDP level data were used primarily, in some cases where CDP data were not available other geographies were used to delineate a community that would otherwise be excluded. MCD level data, for instance, were used when CDP level data were not available for the Northeast and in one instance, Census Tract level data were used because MCD data did not truly represent the consensus boundaries for the community as recognized by agency social scientists. These geographical boundaries can include zipcode and Census Block data in other regions. The use of these other boundaries is consistent with research conducted in many different regions that demonstrated any single geographic definition of fishing community would be difficult, as fishermen can live either in or near ports where they dock and/or unload their catch. Associated businesses and other support activity may also take place within or outside a narrow boundary of community. Where extensive ethnographic research is not available, these boundaries are the best estimates available for data collection purposes.

Not all Census data came from the ACS. The percent water coverage variable was extracted from the Census Bureau's Tigerline files found online at the Topologically Integrated Geographic Encoding and Referencing (TIGER) system (census.gov/geo/www/tiger/). Other data from the 2000 decennial census were also collected for those variables where demographic change over time needed to be calculated.

Several types of data were not as readily accessible and downloadable as census data. Variables for crime and weather hazards were available but not for download, requiring data to be cut and pasted by hand on a community-by-community basis into the database. The crime index variable was collected from CLRsearch.com and weather hazards from Moving.Com. The entire process was extremely tedious and time-consuming. The Environmental Protection Agency (EPA) registered facilities[7] variable, drawn from the EPA Environofacts website, was calculated based on the frequency of registered facilities in each community. Data on the number of boat launches were drawn from the Census County Business

[6] The community name used in the establishment of a CDP is to "be one that is recognized and used in daily communication by the residents of the community." Census Designated Place (CDP) Program for the 2010 Census - Final Criteria, *Federal Register*, February 13, 2008 (Volume 73, Number 30), accessed March 9, 2012.

[7] A registered facility is facilities, sites or places subject to environmental regulations or of environmental interest.

Patterns database using the North American Industry Classification System (NAICS) code for marinas. Each data source underwent an evaluation process in which we attempted to establish the authenticity of the data by identifying the primary source. Other types of data relating to climate change and sea level rise were also researched, but were not found in a format at the community level easily adapted to our needs. This remains an area for further research.

NMFS fisheries data were available for the east coast from both the Northeast and the Southeast Regional Science Centers and Southeast Regional Office. Although the commercial fisheries data (permits, pounds and value landed) were comparable, the NMFS recreational data were more variable. The SERO generates numerous recreational data (vessel designation as commercial or recreational; permits by fishery; and charter and recreational permits by home port and owner address). The Northeast recreational data are limited to federally permitted for-hire charter activity, making regionally comparable recreational indices impossible with NEFSC, SERO and SEFSC data. Neither region has quantitative data on subsistence fishing. However, as described above, a regionally comparable customized database was generated from the *Marine Recreational Fishing Information Program* (MRIP) site surveys[8], using a summation of all estimated fishing trips for sites near a particular community. It includes community level data on recreational fishing pressure (as estimated by the number of trips) representing shore, charter boat (federal and state), and private recreational fishing activity. Further, not all NMFS regions have MRIP. These regional differences in data collection for the recreational fishery mean this measure will need to be calculated on a region-by-region basis until a uniform measure can be developed for all regions.

While these indices are sufficiently robust for the assessment of fishing community vulnerability, additional indices and data on social capital, critical for understanding social networks and social cohesion, would strengthen the analysis. Data on fishing community infrastructure would improve our assessment of community dependence on fishing, both recreational and commercial. Additional variables and indices will also be needed to assess well-being more broadly. Currently, databases for most of these variables are inadequate at the community level. With regard to sea level rise, community level measures of coastal hazards are an area to be explored,. However, as the level of analysis progresses from community, to county, and to state there is increasingly more secondary data; measures of health and well-being, for instance, are more attainable at county and state levels than at the community level and should be researched.. This may allow addition of new variables and indices at different geographic levels that could complement and contextualize the community indicators.

This discussion highlighted issues encountered in the compilation of a cross regional database. Further, such issues to resolve are anticipated to arise as this data collection effort is expanded to include all communities in coastal counties in the U.S. Creating comparable national data will have some challenges, as not all fisheries data is comparable. However, regional analyses will reflect the relative richness of data in each region.

[8] Unfortunately, the state of Texas does not participate in the MRIP program, so there are no recreational fishing engagement or reliance measures for the state. This makes our common recreational measure less robust than is ideal.

IX. Conclusion

We have developed a set of social indicators using secondary data that can improve the analytical rigor of fisheries social impact assessment. The majority of these data are readily accessible and can be compiled quickly to create measures of social vulnerability and to update community profiles. Because we know these communities exist within a larger coastal economy, the ability to profile the context of vulnerability to social factors outside of fishing is critical to understanding how regulatory change will be absorbed into these multifaceted places. Creating social indicators of vulnerability for fishing communities provides a pragmatic approach toward standardization of data and analysis for assessment of some of the long term effects of management actions.

The advantage of this approach is the ability to use secondary data rather than rely on primary data collection. It provides a significant timesaving compared with conducting fieldwork or implementing a survey, an important consideration given the sometimes-short timeframe in which social impact assessments are conducted. These types of measures can be created for communities and other geographic scales and offer the ability to compare across regions. The analysis is comparatively straightforward and can be modified to adapt to changing circumstances and differential regional availability of specific variables within topical areas without compromising the results. Because they are based on existing standard time series data, these measures can also be developed retroactively to allow valuable analyses of change within a community over time as proxies of resilience.

This research forms the initial step in developing more empirical measures to enhance NMFS' ability to understand the dynamics of fishing communities and their ability to recover from disruptive events, whether they are man-made, such as regulatory change, or natural. Lessons learned from this assessment can guide further research and assist in the development of social impact assessment best practices for management actions.

X. References Cited

Adger, N.W., 2006. Vulnerability. *Global Environmental Change* 16:268-281.

Barnett, J. 2003. Adapting to Climate Change in Pacific Island Countries: The Problem of Uncertainty. *World Development* 29:977-993.

Boyd, H. and A. Charles. 2006. Creating Community-Based Indicators to Monitor Sustainability of Local Fisheries. *Ocean & Coastal Management* 49:237-258.

Chambers, R., 1989. Editorial Introduction: Vulnerability, Coping And Policy. *Institute of Development Studies Bulletin* 20 (2):1-7.

Charles, A., C. Brubridge, H. Boyd,, and A. Lavers. 2009. *Fisheries and the Marine Enviroment in Nova Scotia: Searching for Sustainability and Resilience*. Halifax, Nova Scotia: GPI Atlantic.

Clay, P. M., and J. Olson. 2008. Defining "Fishing Communities": Vulnerability and the Magnuson-Stevens Fishery Conservation and Management Act. *Human Ecology Review* 15(2):143-160.

Coastal Enterprises, Inc. 2002. Preserving Commercial Fishing Access: A Study of Working Waterfronts in 25 Maine Communities. Report for the Maine State Planning Office Coastal Program. State Planning Office. State House Station 38, Augusta, Maine 04333-0038.

Cobb, C., and C. Rixford. 1998. *Lessons Learned from the History of Social Indicators*. Pp. 36. San Francisco, CA: Redefining Progress.

Colburn, L. L. and M. Jepson. 2012. Social Indicators of Gentrification Pressure in Fishing Communities: A Context for Social Impact Assessment. *Coastal Management* 40:289-300.

Cox, J., C. Rosenzweig, W. Solecki, R. Goldberg, P. Kinney. 2006. *Social Vulnerability to Climate Change: A Neighborhood Analysis of the Northeast U.S. Megaregion.* A White Paper Drafted for Union of Concerned Scientists, Northeast Climate Change Impact Study.

Cutter, S. L., 1996. Vulnerability to Environmental Hazards. *Progress in Human Geography* 20: 529-539.

Cutter, S. L., L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, and J. Webb. 2008. A Place-Based Model for Understanding Community Resilience to Natural Disasters. *Global Environmental Change* 18 (4):598-606.

Cutter, S.L., C.T. Emrich, J. J. Webb, and D. Morath. Social Vulnerability to Climate Variability Hazards: A Review of the Literature. Final Report to Oxfam America. Hazards and Vulnerability Research Institute. University of South Carolina. Columbia, SC. Pp. 44.

Cutter,.S.L., C. Burton, , and C. T. Emrich. 2010. Disaster Resilience Indicators for Benchmarking Baseline Conditions, *Journal of Homeland Security and Emergency Management*: Vol. 7 : Iss. 1, Article 51.

Cutter, S. L. Byron J., and W. Shirley. 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly* 84(2):242-261.

Cutter, S. L., J. T. Mitchell, and M. S. Scott. 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers* 90(4):713-737.

Davis, A. P., 1996. Targeting the Vulnerable in Emergency Situations: Who is Vulnerable? *Lancet* 348 (9031):686-871.

Degnbol, P. 2005. Indicators as a means of communicating knowledge. Ices Journal of Marine Science 62(3):606-611.

DeYoung, C., A. Charles, and A. Hjort. 2008. Human Dimensions of the Ecosystem Approach to Fisheries: An Overview of Context, Concepts, Tools, and Methods. *In* FAO Fisheries Technical Paper., Vol. No. 489. Rome: FAO, Pp. 152.

Folke, C. 2006. Resilience: The Emergence of a Perspective for Social–Ecological Systems Analyses. *Global Environmental Change* 16:253–267.

Food and Agricultural Organization of the United Nations (FAO), Fishery Resources Division, . 1999 Indicators for sustainabile development of marine capture fisheries. FAO.

Food and Agriculture Organization of the United Nations (FAO). 2008. *FAO Technical Guidelines for Responsible Fisheries* No. 4, Suppl. 3. Rome, FAO. Pp 104.

Fox, K. A. 1986. The Present Status of Objective Social-Indicators - A Review of Theory and Measurement. *American Journal of Agricultural Economics* 68(5):1113-1120.

Gallopín, G.C., 2006. Linkages between Vulnerability, Resilience, and Adaptive Capacity. *Global Environmental Change* 16: 293-303.

Gale, R.P. 1991. Gentrification of America's Coasts: Impacts of the Growth Machine on Commercial Fishermen. Society and Natural Resources. 4:103-121.

Gulf and South Atlantic Fisheries Foundation, Inc. (GSAFFI) 2010. Development of Social Indicators for Fishing Communities of the Southeast: Measures of Dependence, Vulnerability, Resilience, and Gentrification. Lincoln Center, Suite 740, 5401 West Kennedy Blvd., Tampa, Florida 33609-2447.

Gulf of Mexico Fishery Management Council (GMFMC). 2004. Final Environmental Impact Statement for the Generic Essential Fish Habitat Amendment to the Following Fishery Management Plans of the Gulf of Mexico (GOM). Gulf of Mexico Fishery Management Council, Tampa, Florida.

Gulf of Mexico Fishery Management Council (GMFMC). 2005. Amendment Number 13 to the Fishery Management Plan For the Shrimp Fishery of the Gulf Of Mexico, U.S. Waters with Environmental Assessment Regulatory Impact Review, And Regulatory Flexibility Act Analysis. Gulf of Mexico Fishery Management Council, Tampa, Florida.

Hall-Arber, M., C. Dyer, J. Poggie, J. McNally and R. Gagne. 2001. New England's Fishing Communities. MIT Sea Grant College Program. Cambridge, Massachusetts.

Hooghe, M. and B. Vanhoutte. 2010. Subjective Well-Being and Social Capital in Belgian Communities. The Impact of Community Characteristics on Subjective Well-Being Indicators in Belgium. *Social Indicators Research* 100(1):17-36.

Jacob, S. and M. Jepson. 2009. Creating a Community Context for the Fishery Stock Sustainability Index. *Fisheries* 43(5): 228-231.

Jacob, S. P. Weeks, B. Blount, M. Jepson. 2010. Exploring Fishing Dependence in Gulf Coast Communities. *Marine Policy* 34(6):1307-1314.

Jacob, S., P. Weeks, B. Blount, and M. Jepson. 2012. Development and Evaluation of Social Indicators of Vulnerability and Resiliency for Fishing Communities in the Gulf of Mexico. *Marine Policy* 26(10):16-22.

Jepson, M. and S. Jacob. 2007. Social Indicators and Measurements of Vulnerability for Gulf Coast Fishing Communities. *NAPA Bulletin* 28:57-68.
Johnston, D. F., and M. J. Carley. 1981. Social Measurement and Social-Indicators. *Annals of the American Academy of Political and Social Science* 453(JAN):237-253.
Kelly, P. M. and W. N. Adger. 2000. Theory and Practice in Assessing Vulnerability to Climate Change and Facilitating Adaptation. Climatic Change 47 (4):325-352.
Klein, R. J. T. and R. J. Nicholls. 1999. Assessment of Coastal Vulnerability to Climate Change. *Ambio* 28:128-187.
Lamarque, J.C. 2009. *The Making of a Waterfront Suburb: An Ethnography of Coastal Gentrification in New Jersey*. Anthropology, Rutgers, The State University of New Jersey, New Brunswick, NJ.
Lewontin, R. C., 1969. The Meaning of Stability. In: Diversity and Stability of Ecological Systems. *Brookhaven Symposia in Biology* no 22. Brookhaven, New York.
Livingston, P. A., et al. 2005. A Framework for Ecosystem Impacts Assessment Using an Indicator Approach. *Ices Journal of Marine Science* 62(3):592-597.
Magnuson-Stevens Fishery Conservation and Management Act [1996]. U.S. Department of Commerce. NOAA Technical Memorandum NMFSF/SPO-23 December 1996.
Manyena, S. B. 2006. The Concept of Resilience Revisited. *Disasters* 30 (4):433-450.
Marshall, N. A., and P. Marshall. 2007. Conceptualizing and Operationalizing Social Resilience within Commercial Fisheries in Northern Australia. *Ecology and Society* 12(1).
McLeod, J. D., and R. C. Kessler. 1990. Socioeconomic-Status Differences in Vulnerability to Undesirable Life Events. *Journal of Health and Social Behavior* 31(2):162-172.
Mederer, H. 1999. Surviving the Demise of a Way of Life: Stress and Resilience in Northeastern Fishing Families, In *The Dynamics of Resilient Families: Resiliency in Families*, eds. H. I. McCubbin, E. Thompson, A. I. Thompson, and J. A. Futrell , Vol. 4: 203-235. California Thousand Oaks : Sage Publications.
Millennium Ecosystem Assessment (MEA). 2005a. *Ecosystems and Human Well-being: A Framework for Assessment*. http://www.millenniumassessment.org/en/Framework.aspx
Millennium Ecosystem Assessment (MEA). 2005b. *Ecosystems and Human Well-being: Synthesis*. http:/www.millenniumassessment.org/documents/document.356.aspx.pdf
Moser, S. C., 2010. Now More than Ever: The Need for More Societally Relevant Research on Vulnerability and Adaptation to Climate Change. *Applied Geography* 30: 464-474.
Moser, C. O. N., 1998. The Asset Vulnerability Framework: Reassessing Urban Poverty Reduction Strategies. *World Development* 26 (1):1-19.
Norman, K., J. Sepez, H. Lazrus, N. Milne, C. Package, S. Russell, K. Grant, R. P. Lewis, J. Primo, E. Springer, M. Styles, B. Tilt, and I. Vaccaro. 2007. Community Profiles for West Coast and North Pacific Fisheries. NOAA Technical Memorandum NMFS-SWFSC-65. U.S. Department of Commerce, NOAA, NMFS, Northwest Fisheries Science Center, Seattle, WA.
O'Keefe, P., K. Westgate, and B. Wisner. 1976. Taking the Naturalness out of Natural Disasters. *Nature* 260:566-567.
Oliver-Smith, A. 1996. Anthropological research on hazards and disasters. *Annual Review of Anthropology* 25:303-328.
Paterson, B., et al. 2010. Transdisciplinary Co-Operation for an Ecosystem Approach to Fisheries: A Case Study from the South African Sardine Fishery. *Marine Policy* 34(4):782-794.

Pacific Fishery Management Council (PFMC). 2006. Final Environmental Impact Statement for the Proposed Acceptable Biological Catch and Optimum Yield Specifications and Management Measures for the 2007-2008 Pacific Coast Groundfish Fishery and Amendment 16-4: Rebuilding Plans for Seven Depleted Pacific Coast Groundfish Species.

Peterson, G., C. R. Allen, and C. S. Holling. 1998. Ecological Resilience, Biodiversity, and Scale. *Ecosystems* 1:6-18.

Pollnac, R. B., S. Abbott-Jamieson, C. Smith, M. L. Miller, P. M. Clay, and B. Oles. (2006[2008]) Toward a Model for Fisheries Social Impact Assessment, *Marine Fisheries Review* 68:1-18.

Pollnac, Richard B. (2012) Taxonomy of NE and SE Region Fishing Communities in Terms of Vulnerability/Resilience Indicators II. Vulnerability Working Report #3. Kingston, RI: Department of Marine Affairs.

Porter, J.. 2011. A Simplified Indicator of Social Well-Being in the United States: Examining the Ecological Impact of Family Formation within a County Level Framework. *Social Indicators Research*:1-20. (Online First).

Sarracino, F. 2011. Money, Sociability and Happiness: Are Developed Countries Doomed to Social Erosion and Unhappiness? *Social Indicators Research*:1-54 (Online First).

Schmidtlein, M. C., R. C. Deutsch, W. W. Piegorsch, and S. L. Cutter. 2008. A Sensitivity Analysis of the Social Vulnerability Index. *Risk Analysis* 28(4):1099-1114.

Schneider, M. 1976. The “Quality of Life” and Social Indicators Research. *Public Administration Review*. 36(3):297-305.

Sherrieb, K., F. H. Norris, and S. Galea. 2010. Measuring Capacities for Community Resilience. *Social Indicators Research* 99(2):227-247.

Smith, C. L. and P. M. Clay. 2010. Measuring Subjective and Objective Well-being: Analysis from Five Marine Commercial Fisheries. *Human Organization* 69(2):158-168.

Smith, S. D., S. Jacob, and M. Jepson. 2003. The Stress Process in Florida's Commercial Fishing Families. *Society and Natural Resources* 16(1):39-59.

Smith, S. L., R. B. Pollnac, L. L. Colburn and J. Olson. 2011. Classification of Coastal Communities Reporting Commercial Fish Landings in the Northeast Region: Developing and Testing a Methodology. *Marine Fisheries Review* 73(2):41-61.

Stiglitz J.E., A. Sen, and J-P. Fitoussi. 2009. "Report by the Commission on the Measurement of Economic Performance and Social Progress, CMEPSP, September, 14, 2009." Pp. 291, Commission on the Measurement of Economic Performance and Social Progress. http://www.stiglitz-sen-fitoussi.fr/en/documents.htm.

Tuler, S., J. Agyeman, P. Pinto da Silva, K. R. LoRusso, and R. Kay. 2008. Assessing Vulnerabilities: Integrating Information About Driving Forces that Affect Risks and Resilience in Fishing Communities. *Human Ecology Review* 15 (2):171-184.

Turner II, B. L., R.E. Kasperson, P. Matson, J.J McCarthy, R.W. Corell, L. Christensen, N. Eckley, J.X. Kasperson, A. Luers, M.L. Martello, C. Polsky, A. Pulsipher, and A. Schiller. 2003. Framework for Vulnerability Analysis in Sustainability Science. *Proc. Natl. Acad. Sci.* USA 100:8074-8079.

Walker, B. H., C. S. Holling, S. R. Carpenter, and A. Kinzig. 2004. Resilience, Adaptability and Transformability in Social-Ecological Systems. *Ecology and Society* 9 (2): 5 [online] URL:http://www.ecologyandsociety.org/vol9/iss2/art5.

Watts, M. and H. G. Bohle, 1993. The Space of Vulnerability: The Causal Structure of Hunger and Famine. *Progress in Human Geography* 17 (1):43-67.
White, G. F., and J. E. Haas. 1975. *Assessment of Research on Natural Hazards*. MIT Press, Cambridge, MA.

XI. Appendices

Appendix 1. Index Tables and Maps

Table A-1. Personal Disruptions Index.

Community	Percentage unemployed	Crime index	Percentage with no diploma	Percent in Poverty	Percentage females separated	Personal Disruptions Index Score
Gulfport, MS (13)	6.0	137	11.6	18.2	16.1	**2.122**
Bayou La Batre, AL (32)	7.5	82	15.8	22.8	9.7	**1.918**
New Bedford, MA (34)	6.0	151	15.5	22.2	4.7	**1.483**
Port Arthur, TX (4)	6.2	124	14.4	23.4	5.3	**1.455**
Biloxi, MS (14)	4.4	99	9.8	12.6	13.5	**1.280**
Houma, LA (10)	2.8	87	15.8	16.4	2.9	0.578
Ocean City, MD (14))	2.4	383	7.0	9.0	1.3	0.567
Cushing, ME (4)	5.7	48	12.6	20.9	0.0	0.472
Orange Beach, AL (20)	2.7	150	1.1	5.3	12.7	0.428
Cameron, LA (32)	0.0	143	18.2	18.6	0.0	0.420
Marathon, FL (14)	2.3	165	7.2	10.7	4.2	0.197
Stonington, ME (10)	2.4	59	15.3	6.9	3.4	0.106
Newport, RI (21)	2.6	202	4.7	10.6	1.5	-0.048
Port Aransas, TX (25)	0.9	151	8.7	14.0	0.9	-0.089
St. Marks, FL (33)	0.0	135	11.5	4.8	4.3	-0.107
Point Judith, RI (22)	4.1	2	4.7	19.6	0.6	-0.283
Virginia Beach, VA (18)	3.1	62	5.5	6.9	2.9	-0.413
Seabrook, NH (25)	3.1	6	9.6	7.2	0.5	-0.572
Wanchese, NC (32)	0.0	115	1.8	9.0	3.2	-0.664
Barnegat Light, NJ (22)	1.8	53	2.0	4.5	0.4	-1.096
Factor Loading	**0.628**	**0.477**	**0.786**	**0.811**	**0.600**	
Percentage Explained Variation	**45.00**	Index scores in bold are at or above threshold of one standard deviation				
Theta Reliability	**0.640**					
Eigenvalue	**2.231**					

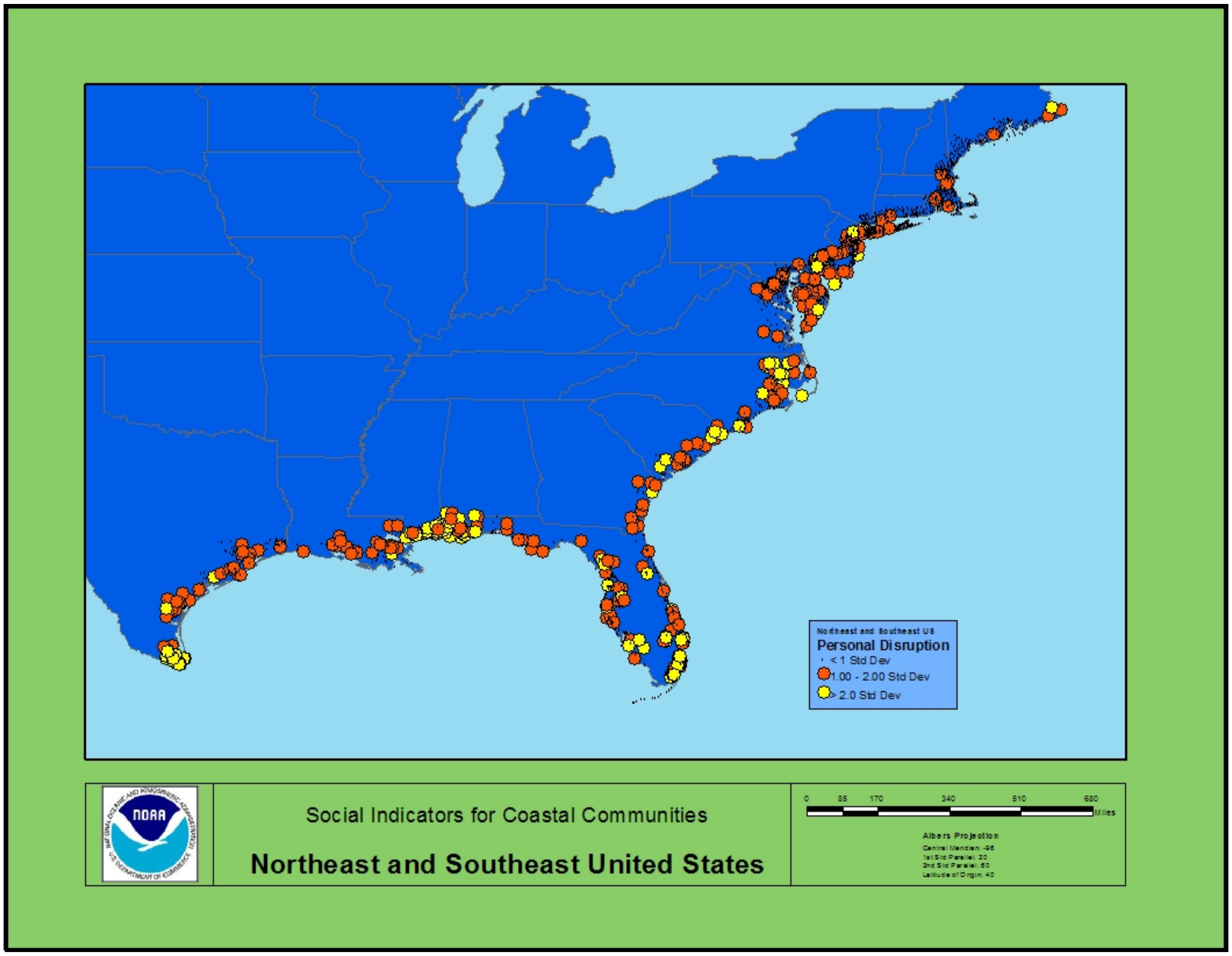

Figure A-1. Personal Disruptions Index.

Table A-2. Population Composition Vulnerability Index.

Community	Percent white alone	Percent female single headed households	Population age 0-5	Percent Speak English less than very well	Population Composition Vulnerability Index Score
Port Arthur, TX (4)	27.8	20.5	7.4	13.9	**1.500**
Bayou La Batre, AL (32)	59.4	9.9	11.1	18.3	**1.063**
New Bedford, MA (34)	70.8	21.1	7.2	17.0	**0.974**
Gulfport, MS (13)	56.5	21.4	8.3	2.6	0.775
Houma, LA (10)	66.9	16.4	7.7	2.6	0.352
Biloxi, MS (14)	67.5	15.1	6.4	4.4	0.238
Virginia Beach, VA (18)	66.6	13.3	7.1	3.8	0.215
Marathon, FL (14)	72.5	6.8	7.4	12.0	0.175
Wanchese, NC (32)	100.0	9.4	9.6	0.0	-0.370
Newport, RI (21)	88.1	10.5	4.4	2.2	-0.527
Cushing, ME (4)	98.1	6.6	6.1	0.0	-0.772
Stonington, ME (10)	97.0	6.9	5.3	0.5	-0.796
Point Judith, RI (22)	96.4	7.5	3.5	3.8	-0.801
Seabrook, NH (25)	96.1	7.0	4.4	0.8	-0.847
Port Aransas, TX (25)	85.7	5.4	2.4	3.1	-0.853
Cameron, LA (32)	86.9	12.1	0.0	0.0	-0.912
St. Marks, FL (33)	92.3	10.0	0.0	0.0	-1.083
Orange Beach, AL (20)	93.2	4.6	1.3	3.0	-1.101
Ocean City, MD (14))	97.0	2.3	1.9	3.7	-1.178
Barnegat Light, NJ (22)	98.6	2.9	2.2	0.9	-1.252
Factor Loading	**-0.898**	**0.719**	**0.675**	**0.739**	
Percentage Explained Variation	**58.120**	Index scores in bold are at or above threshold of one standard deviation			
Theta Reliability	**0.640**				
Eigenvalue	**2.231**				

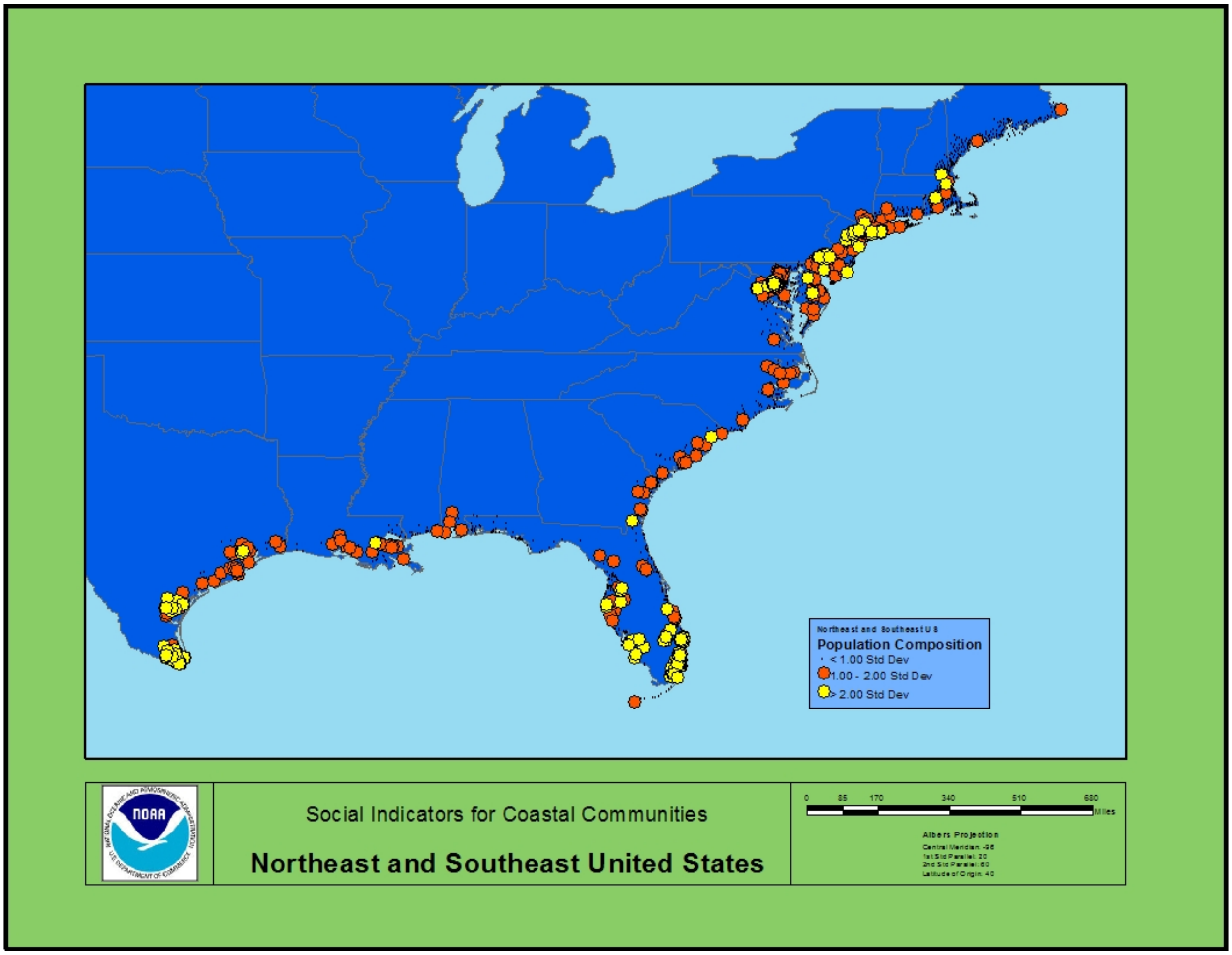

Figure A-2. Population Composition Vulnerability Index.

Table A-3. Poverty Index.

Community	Percent receiving assistance	Per cent of families below poverty level	Percentage 65 and over in poverty	Percent people under 18 in poverty	Poverty Index Score
New Bedford, MA (34)	7.1	18.9	14.3	34.0	**1.574**
Cameron, LA (32)	0.0	20.4	24.0	36.0	**1.417**
Port Arthur, TX (4)	2.6	19.5	19.1	31.7	**1.332**
Cushing, ME (4)	2.1	19.1	10.3	45.5	**1.309**
Bayou La Batre, AL (32)	1.4	21.4	22.5	23.8	**1.240**
Wanchese, NC (32)	2.8	5.2	39.5	13.3	**0.978**
Gulfport, MS (13)	3.5	14.1	12.6	25.6	0.821
Port Aransas, TX (25)	0.9	11.2	8.2	32.4	0.498
Houma, LA (10)	0.8	13.1	12.4	21.8	0.460
Biloxi, MS (14)	3.0	9.6	10.0	15.2	0.260
Newport, RI (21)	1.3	5.1	12.1	13.2	-0.050
Marathon, FL (14)	0.2	8.5	7.9	14.9	-0.094
Seabrook, NH (25)	3.6	3.5	4.7	8.5	-0.281
Virginia Beach, VA (18)	1.0	5.1	4.9	10.0	-0.386
Ocean City, MD (14))	0.3	6.6	4.7	7.9	-0.435
Point Judith, RI (22)	2.4	3.8	6.0	3.6	-0.439
Orange Beach, AL (20)	0.0	3.4	2.2	10.3	-0.622
St. Marks, FL (33)	0.0	0.0	12.8	0.0	-0.660
Stonington, ME (10)	0.0	0.6	6.9	5.4	-0.701
Barnegat Light, NJ (22)	1.0	2.6	4.8	1.2	-0.701
Factor Loading	**0.544**	**0.915**	**0.716**	**0.862**	
Percentage Explained Variation	**59.720**	Index scores in bold are at or above threshold of one standard deviation if rounded			
Theta Reliability	**0.939**				
Eigenvalue	**3.397**				

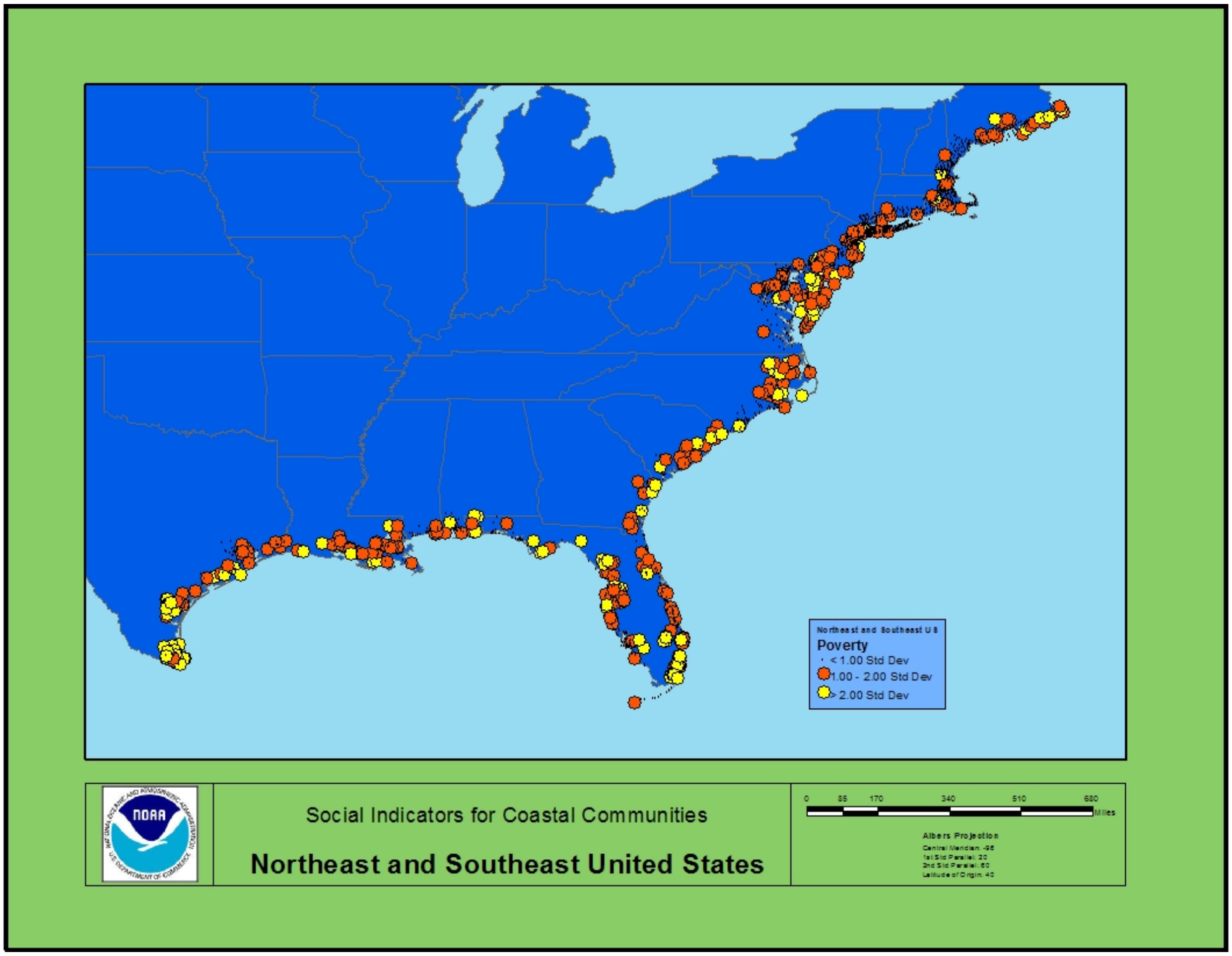

Figure A-3. Poverty Index.

Table A-4. Labor Force Structure Index.

Community	Percent of Class of Worker Self Employed	Percent Labor force	Percent females employed	Percent people receiving Social Security	Labor Force Structure Index Score*
Barnegat Light, NJ (22)	9.7	46.5	37.0	61.2	**1.716**
Ocean City, MD (14))	6.9	46.3	38.2	49.2	**1.332**
Stonington, ME (10)	48.9	63.5	52.4	37.2	**0.950**
Port Arthur, TX (4)	5.9	54.0	40.6	34.1	0.627
Orange Beach, AL (20)	4.5	54.2	45.1	39.9	0.610
Port Aransas, TX (25)	10.8	58.1	54.6	44.5	0.463
Houma, LA (10)	5.1	58.2	46.8	32.7	0.270
Cushing, ME (4)	22.5	65.4	52.2	31.6	0.220
Gulfport, MS (13)	7.0	61.9	48.5	28.0	0.028
Bayou La Batre, AL (32)	4.9	60.7	55.2	34.0	-0.017
Point Judith, RI (22)	8.5	62.6	53.7	31.5	-0.023
Marathon, FL (14)	12.2	63.6	56.8	32.3	-0.046
New Bedford, MA (34)	4.2	61.7	51.8	30.0	-0.066
Seabrook, NH (25)	9.2	64.5	58.8	35.3	-0.117
Biloxi, MS (14)	5.4	67.3	53.6	28.8	-0.296
St. Marks, FL (33)	15.7	74.9	69.1	37.5	-0.544
Newport, RI (21)	8.0	70.1	60.1	25.3	-0.602
Cameron, LA (32)	15.0	70.2	70.0	29.3	-0.642
Virginia Beach, VA (18)	4.7	72.7	60.5	21.1	-0.866
Wanchese, NC (32)	14.4	79.8	81.5	17.3	-1.578
Factor Loading	**-0.355**	**0.951**	**0.905**	**-0.872**	
Percentage Explained Variation	**65.25**	Index scores in bold are at or above threshold of one standard deviation if rounded. * Scores reversed to ensure directional continuity with other scales.			
Theta Reliability	**0.821**				
Eigenvalue	**2.601**				

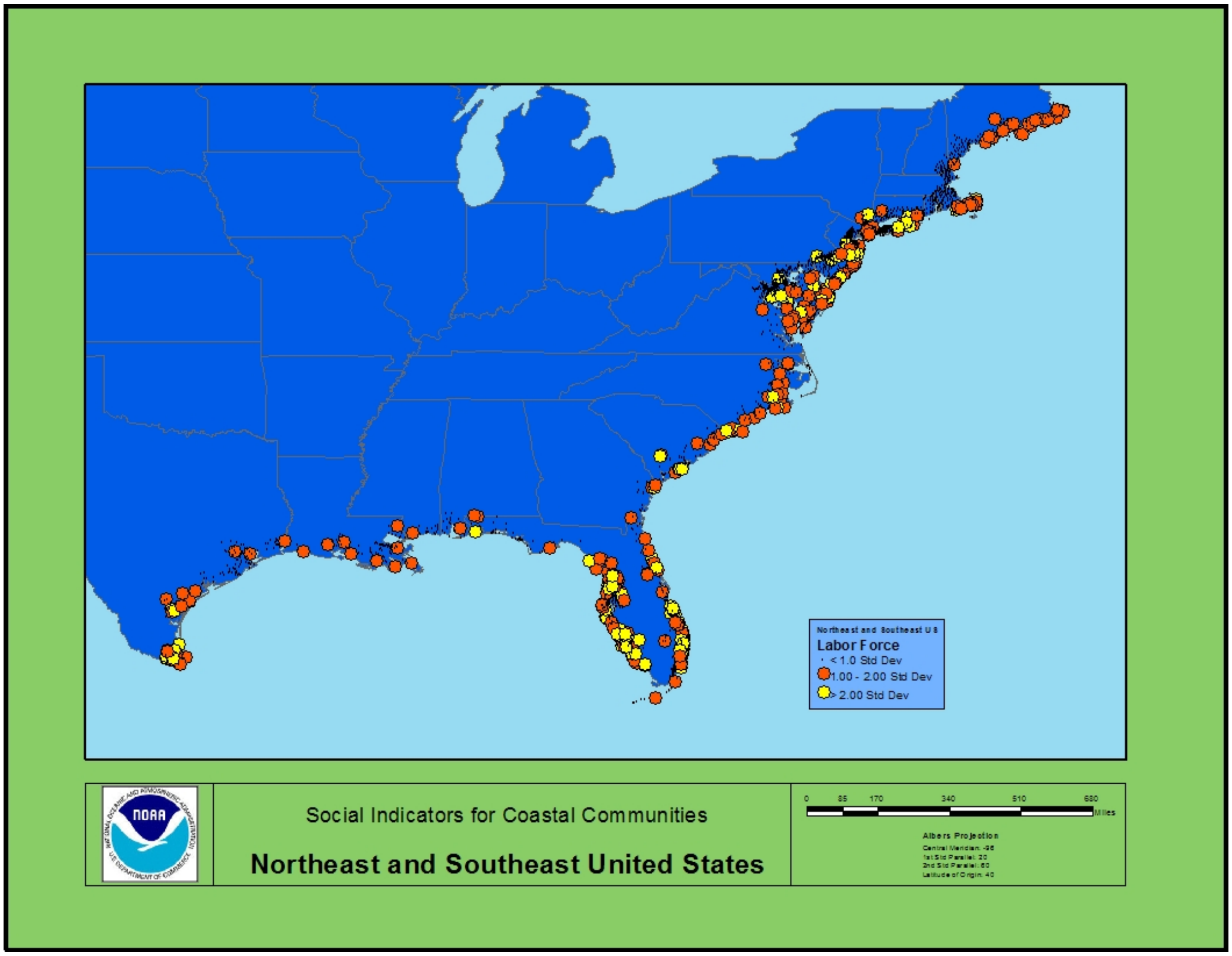

Figure A-4. Labor Force Structure Index.

Table A-5. Housing Characteristics Index.

Community	Median gross rent	Median mortgage	Median number of rooms	Percent Mobile Homes	Housing Structure Index Score*
Cameron, LA (32)	.	1,007.0	5.0	38.3	**1.365**
Stonington, ME (10)	471.0	1,244.0	5.0	15.1	**1.315**
Bayou La Batre, AL (32)	306.0	928.0	5.0	8.2	**1.284**
Cushing, ME (4)	688.0	1,047.0	5.0	18.8	**1.165**
St. Marks, FL (33)	817.0	1,125.0	5.0	23.8	**1.149**
Port Arthur, TX (4)	550.0	942.0	5.0	1.0	**1.008**
Ocean City, MD (14))	838.0	1,559.0	4.0	5.0	**0.987**
Houma, LA (10)	611.0	1,220.0	5.0	5.5	0.794
Seabrook, NH (25)	959.0	1,856.0	5.0	21.8	0.769
Biloxi, MS (14)	775.0	1,285.0	5.0	8.1	0.758
Wanchese, NC (32)	883.0	1,350.0	6.0	25.5	0.739
Gulfport, MS (13)	821.0	1,076.0	5.0	6.4	0.716
Marathon, FL (14)	923.0	2,387.0	4.0	16.2	0.605
Port Aransas, TX (25)	957.0	1,931.0	4.0	8.6	0.561
New Bedford, MA (34)	717.0	1,663.0	5.0	0.4	0.457
Orange Beach, AL (20)	908.0	2,250.0	4.0	7.1	0.358
Newport, RI (21)	1,021.0	1,964.0	5.0	0.8	0.003
Point Judith, RI (22)	1,161.0	1,848.0	5.0	0.8	-0.135
Virginia Beach, VA (18)	1,101.0	1,666.0	6.0	1.0	-0.170
Barnegat Light, NJ (22)	1,123.0	2,453.0	6.0	1.9	-0.643
Factor Loading	**0.814**	**0.882**	**0.751**	**-0.648**	
Percentage Explained Variation	**60.60**	Index scores in bold are at or above threshold of one standard deviation if rounded. * Scores reversed to ensure directional continuity with other scales. Missing data were replaced with the mean.			
Theta Reliability	**0.793**				
Eigenvalue	**2.476**				

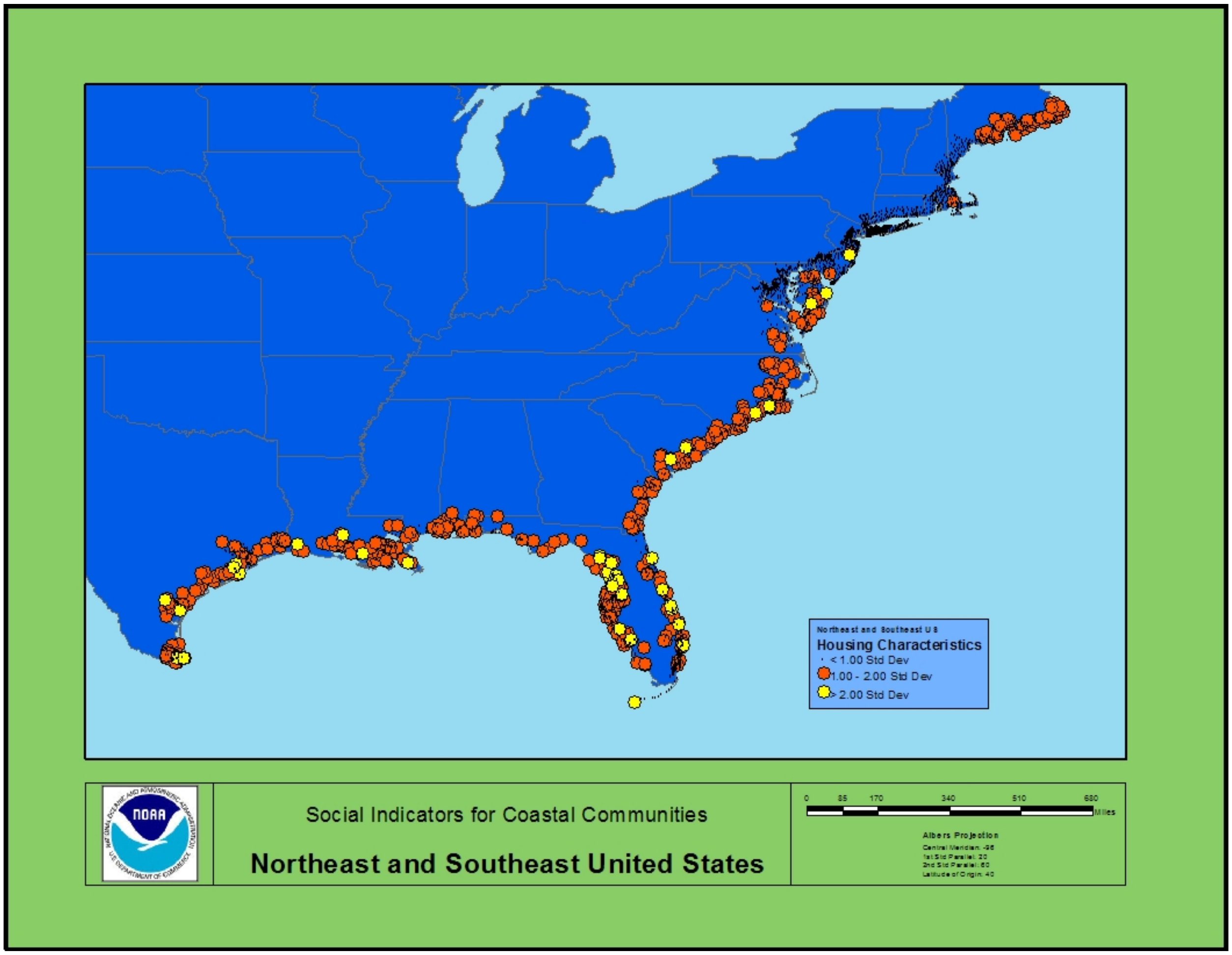

Figure A-5. Housing Characteristics Index.

Table A-6. Housing Disruptions Index.

Community	Percent change in mortgage 2000-2010	Percent change in home value 2000-2010	Owner's monthly cost over 35% of income	Housing Disruptions Index Score
Marathon, FL (14)	81.1	100.4	-0.8	**1.530**
Orange Beach, AL (20)	111.3	97.3	-22.6	**1.428**
Barnegat Light, NJ (22)	46.0	169.0	-64.5	**0.962**
Stonington, ME (10)	74.0	105.0	-69.0	0.880
New Bedford, MA (34)	63.0	118.0	-2.0	0.728
Port Aransas, TX (25)	84.1	82.0	19.4	0.476
Newport, RI (21)	44.0	168.0	-10.0	0.453
Ocean City, MD (14))	41.0	139.0	-41.0	0.279
Point Judith, RI (22)	45.0	154.0	-98.0	0.223
St. Marks, FL (33)	52.0	68.0	-61.0	0.218
Wanchese, NC (32)	53.2	169.6	22.6	0.069
Virginia Beach, VA (18)	44.0	118.0	-3.0	0.007
Seabrook, NH (25)	44.0	48.0	-97.0	-0.339
Port Arthur, TX (4)	50.2	46.8	4.5	-0.378
Biloxi, MS (14)	48.0	62.1	-15.5	-0.545
Bayou La Batre, AL (32)	36.3	47.8	-29.8	-0.548
Houma, LA (10)	49.9	67.9	2.2	-0.582
Cushing, ME (4)	22.0	47.0	-62.0	-0.729
Gulfport, MS (13)	34.7	47.9	-6.8	-0.791
Cameron, LA (32)	56.1	47.0	-100.0	-1.130
Factor Loading	**0.801**	**0.810**	**0.540**	
Percentage Explained Variation	**53.00**	Index scores in bold are at or above threshold of one standard deviation if rounded.		
Theta Reliability	**0.557**			
Eigenvalue	**1.590**			

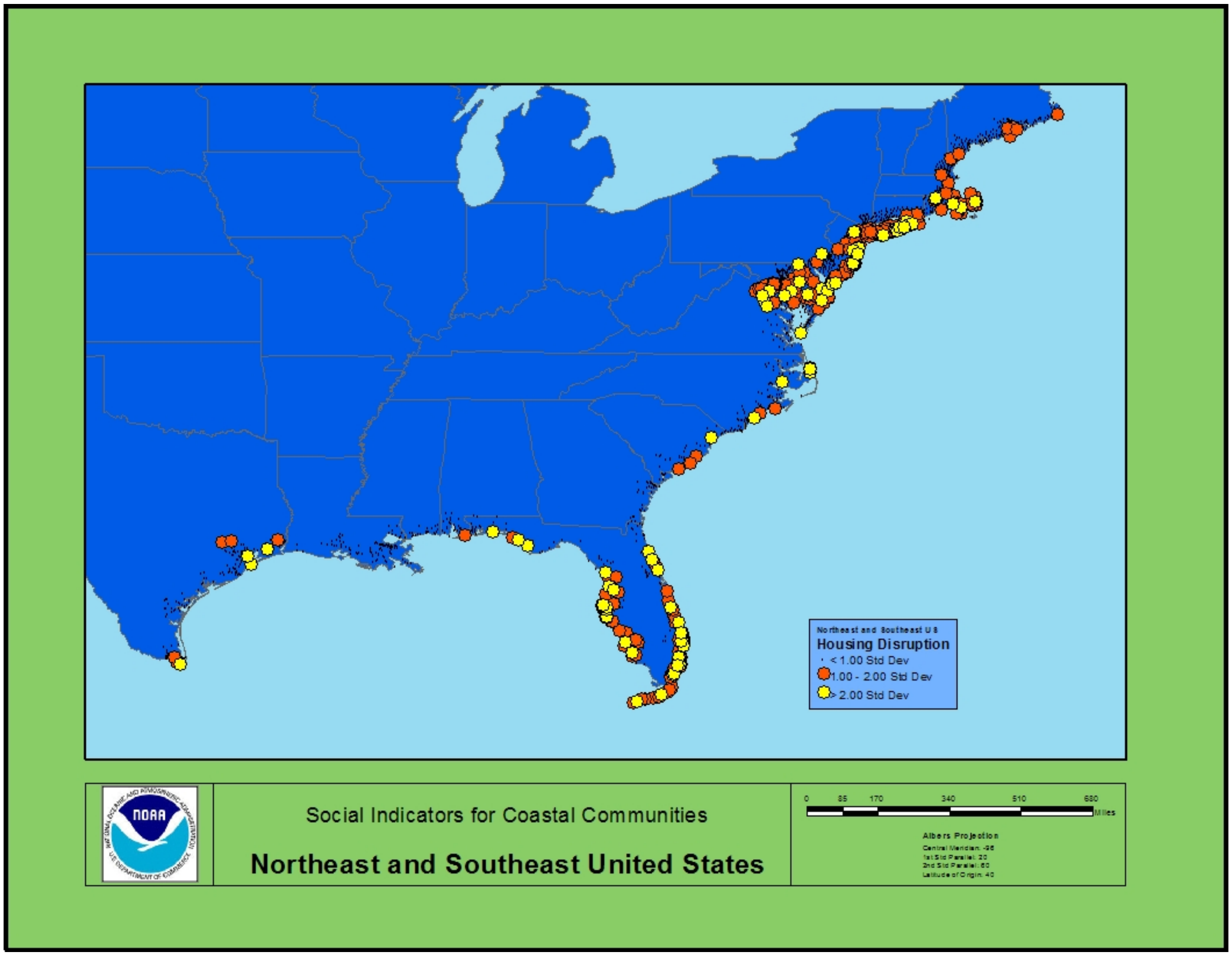

Figure A-6. Housing Disruptions Index.

Table A-7. Retiree Migration Index.

Community	Percent of Households with persons 65 and over	Percent people receiving Social Security	Percent people receiving Retirement Income	Percent in Labor Force	Retiree Migration Index Score
Barnegat Light, NJ (22)	56.4	61.2	39.3	46.5	**2.137**
Ocean City, MD (14))	46.9	49.2	34.3	46.3	**1.523**
Orange Beach, AL (20)	38.1	39.9	28.1	54.2	0.764
Port Aransas, TX (25)	31.5	44.5	25.5	58.1	0.557
Port Arthur, TX (4)	28.6	34.1	17.0	54.0	0.133
Seabrook, NH (25)	31.3	35.3	22.9	64.5	0.127
Stonington, ME (10)	34.9	37.2	14.6	63.5	0.064
Cushing, ME (4)	32.8	31.6	21.1	65.4	0.011
Point Judith, RI (22)	27.6	31.5	19.6	62.6	-0.084
Houma, LA (10)	26.0	32.7	13.6	58.2	-0.145
Marathon, FL (14)	26.4	32.3	17.9	63.6	-0.161
Biloxi, MS (14)	24.1	28.8	25.6	67.3	-0.182
Gulfport, MS (13)	23.3	28.0	19.6	61.9	-0.246
Bayou La Batre, AL (32)	20.3	34.0	15.9	60.7	-0.247
New Bedford, MA (34)	24.7	30.0	15.1	61.7	-0.279
St. Marks, FL (33)	31.7	37.5	14.2	74.9	-0.282
Newport, RI (21)	23.1	25.3	17.6	70.1	-0.556
Cameron, LA (32)	31.5	29.3	2.5	70.2	-0.662
Virginia Beach, VA (18)	18.9	21.1	22.6	72.7	-0.680
Wanchese, NC (32)	14.5	17.3	16.1	79.8	-1.202
Factor Loading	**0.950**	**0.951**	**0.766**	**-0.866**	
Percentage Explained Variation	**78.59**	Index scores in bold are at or above threshold of one standard deviation if rounded.			
Theta Reliability	**0.907**				
Eigenvalue	**3.143**				

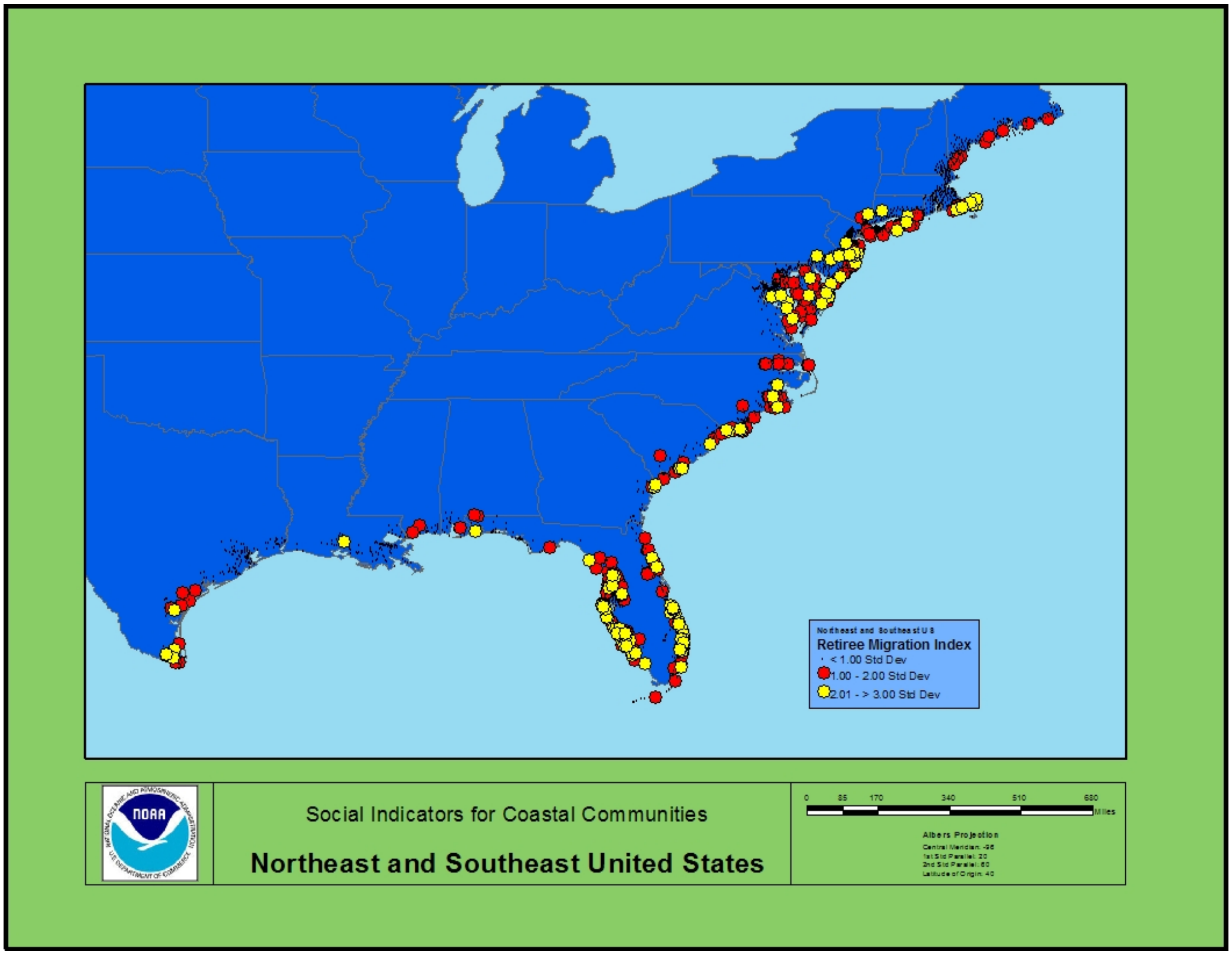

Figure A-7. Retiree Migration Index.

Table A-8. Urban Sprawl Index.

Community	Population Density	Cost of Living	Nearest City w Population 50,000	Median Home Value	Urban Sprawl Index Score
Barnegat Light, NJ (22)	723.0	126.0	0.0	847,550	**1.472**
New Bedford, MA (34)	4,568.0	135.0	0.0	248,500	0.678
Newport, RI (21)	3,158.0	118.0	16.8	433,600	0.419
Seabrook, NH (25)	955.0	135.0	13.8	270,900	0.415
Point Judith, RI (22)	1,193.0	109.0	19.8	416,700	0.123
Virginia Beach, VA (18)	1,747.0	99.0	0.0	268,600	-0.076
Orange Beach, AL (20)	375.1	89.0	23.3	403,500	-0.376
Biloxi, MS (14)	966.8	89.0	0.0	150,100	-0.506
Gulfport, MS (13)	1,093.4	89.0	0.0	118,800	-0.559
Port Aransas, TX (25)	267.9	89.0	21.0	201,100	-0.716
Marathon, FL (14)	1,045.7	102.0	77.3	446,000	-0.724
Port Arthur, TX (4)	371.5	82.0	0.0	52,700	-0.846
St. Marks, FL (33)	109.2	85.0	20.6	142,300	-0.903
Ocean City, MD (14))	1,595.0	92.0	75.4	364,100	-1.009
Bayou La Batre, AL (32)	381.9	84.0	18.5	67,700	-1.026
Houma, LA (10)	2,223.8	86.0	40.4	137,700	-1.075
Cushing, ME (4)	73.0	91.0	54.9	170,800	-1.177
Cameron, LA (32)	23.6	81.0	30.1	77,300	-1.219
Wanchese, NC (32)	276.1	83.0	72.8	282,800	-1.349
Stonington, ME (10)	99.0	90.0	87.2	197,900	-1.565
Factor Loading	**0.387**	**0.894**	**-0.589**	**0.819**	
Percentage Explained Variation	**49.10**	Index scores in bold are at or above threshold of one standard deviation if rounded.			
Theta Reliability	**0.602**				
Eigenvalue	**1.973**				

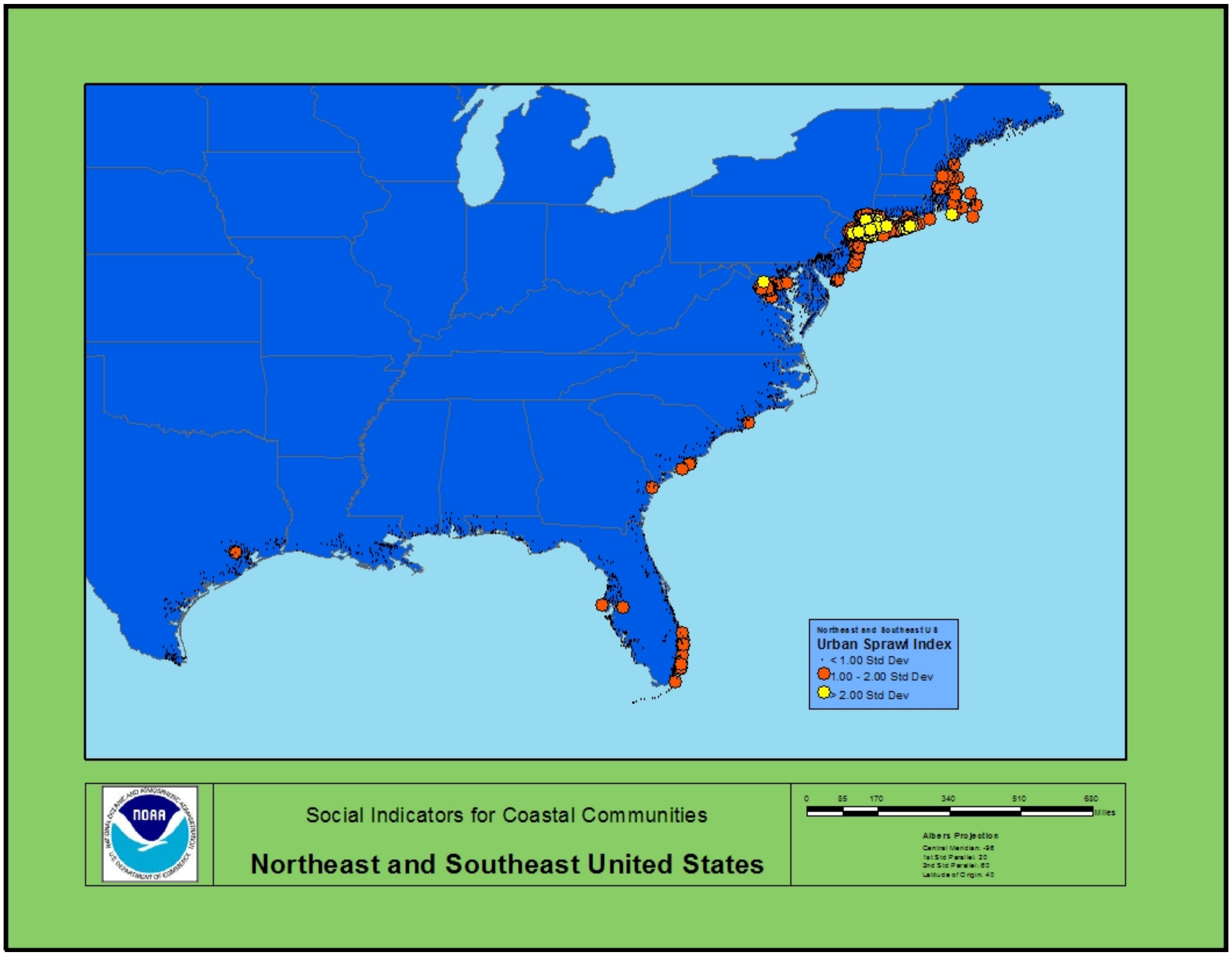

Figure A-8. Urban Sprawl Index.

Table A-9. Natural Amenities Index.

Community	Percent of rentals vacant	Percent of all housing vacant	Number of boat launches per 1,000 persons	Percent of watercoverage	Natural Amenities Index Score
Ocean City, MD (14))	90.3	85.9	2.1	0.9	**4.563**
St. Marks, FL (33)	0.0	30.2	24.0	0.4	**3.773**
Orange Beach, AL (20)	71.6	76.8	0.0	7.8	**3.542**
Barnegat Light, NJ (22)	58.6	79.4	2.9	0.4	**3.490**
Port Aransas, TX (25)	45.6	55.6	0.0	36.5	**2.828**
Marathon, FL (14)	7.8	40.7	2.2	9.0	0.941
Stonington, ME (10)	10.4	48.7	1.0	0.7	0.851
Port Arthur, TX (4)	5.4	14.7	0.0	46.6	0.725
Cameron, LA (32)	.	16.5	4.3	9.3	0.714
Biloxi, MS (14)	14.2	18.4	0.1	18.1	0.460
Wanchese, NC (32)	7.2	17.9	2.0	14.9	0.451
Point Judith, RI (22)	7.4	30.3	1.3	0.6	0.324
Gulfport, MS (13)	13.0	16.8	0.1	13.1	0.266
Cushing, ME (4)	5.1	33.8	0.0	0.3	0.126
Seabrook, NH (25)	11.8	15.8	0.4	7.9	0.120
Newport, RI (21)	7.4	22.8	0.4	0.3	-0.011
Bayou La Batre, AL (32)	7.6	21.6	0.0	1.9	-0.065
Houma, LA (10)	5.5	10.8	0.0	1.5	-0.416
New Bedford, MA (34)	5.8	9.3	0.1	0.2	-0.462
Virginia Beach, VA (18)	4.4	6.7	0.0	0.5	-0.577
Factor Loading	**0.770**	**0.824**	**0.605**	**0.493**	
Percentage Explained Variation	**48.80**	Index scores in bold are at or above threshold of one standard deviation if rounded. Missing data were replaced with the mean.			
Theta Reliability	**0.620**				
Eigenvalue	**1.874**				

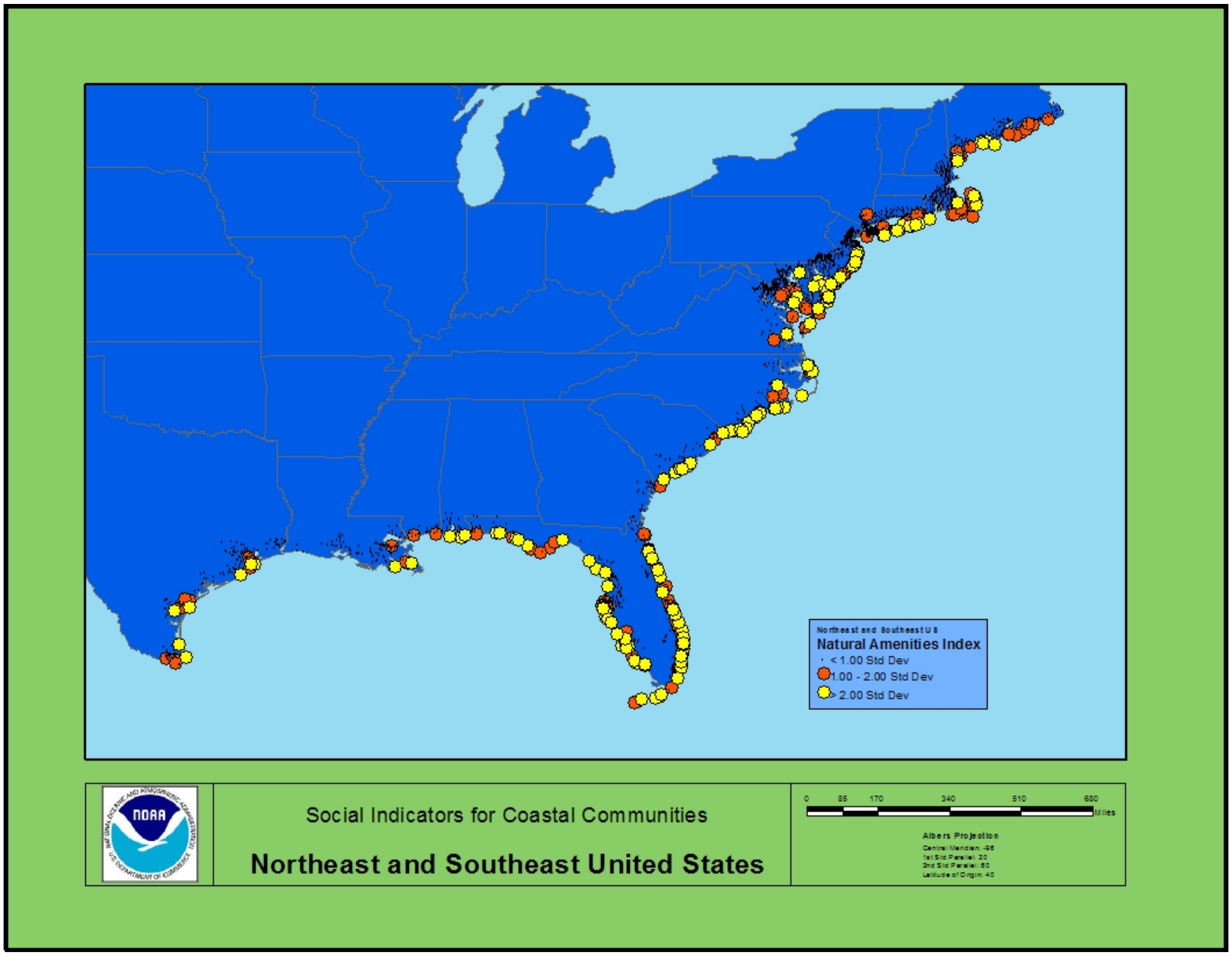

Figure A-9. Natural Amenities Index.

Table A-10. Recreational Fishing Reliance Index.

Community	Recreational fishing mode charter by population	Recreational fishing mode private by population	Recreational fishing mode shore by population	Recreational Fishing Reliance Index Score
Virginia Beach, VA (18)	0.0	974.7	849.0	**10.845**
St. Marks, FL (33)	21.3	500.8	75.8	**5.219**
Marathon, FL (14)	1.4	649.1	204.6	**4.752**
Ocean City, MD (14))	4.3	260.7	414.2	**4.443**
Point Judith, RI (22)	0.9	182.3	495.8	**4.213**
Orange Beach, AL (20)	5.8	243.7	149.0	**2.658**
Biloxi, MS (14)	0.2	230.2	245.5	**2.651**
Barnegat Light, NJ (22)	4.0	272.4	148.8	**2.618**
Gulfport, MS (13)	0.0	161.9	214.2	**2.046**
Newport, RI (21)	0.0	68.0	187.0	**1.355**
Seabrook, NH (25)	2.0	68.3	80.9	0.832
Wanchese, NC (32)	4.2	119.2	0.0	0.785
New Bedford, MA (34)	0.0	52.0	76.6	0.498
Cameron, LA (32)	0.0	67.4	23.0	0.205
Bayou La Batre, AL (32)	0.0	40.6	28.5	0.100
Stonington, ME (10)	0.0	0.0	3.4	-0.294
Houma, LA (10)	0.0	0.0	0.0	-0.317
Cushing, ME (4)	0.0	0.0	0.0	-0.317
Port Aransas, TX (25)	0.0	0.0	0.0	-0.317
Port Arthur, TX (4)	0.0	0.0	0.0	-0.317
Factor Loading	**0.352**	**0.917**	**0.897**	
Percentage Explained Variation	**58.97**	Index scores in bold are at or above threshold of one standard deviation if rounded.		
Theta Reliability	**0.653**			
Eigenvalue	**1.769**			

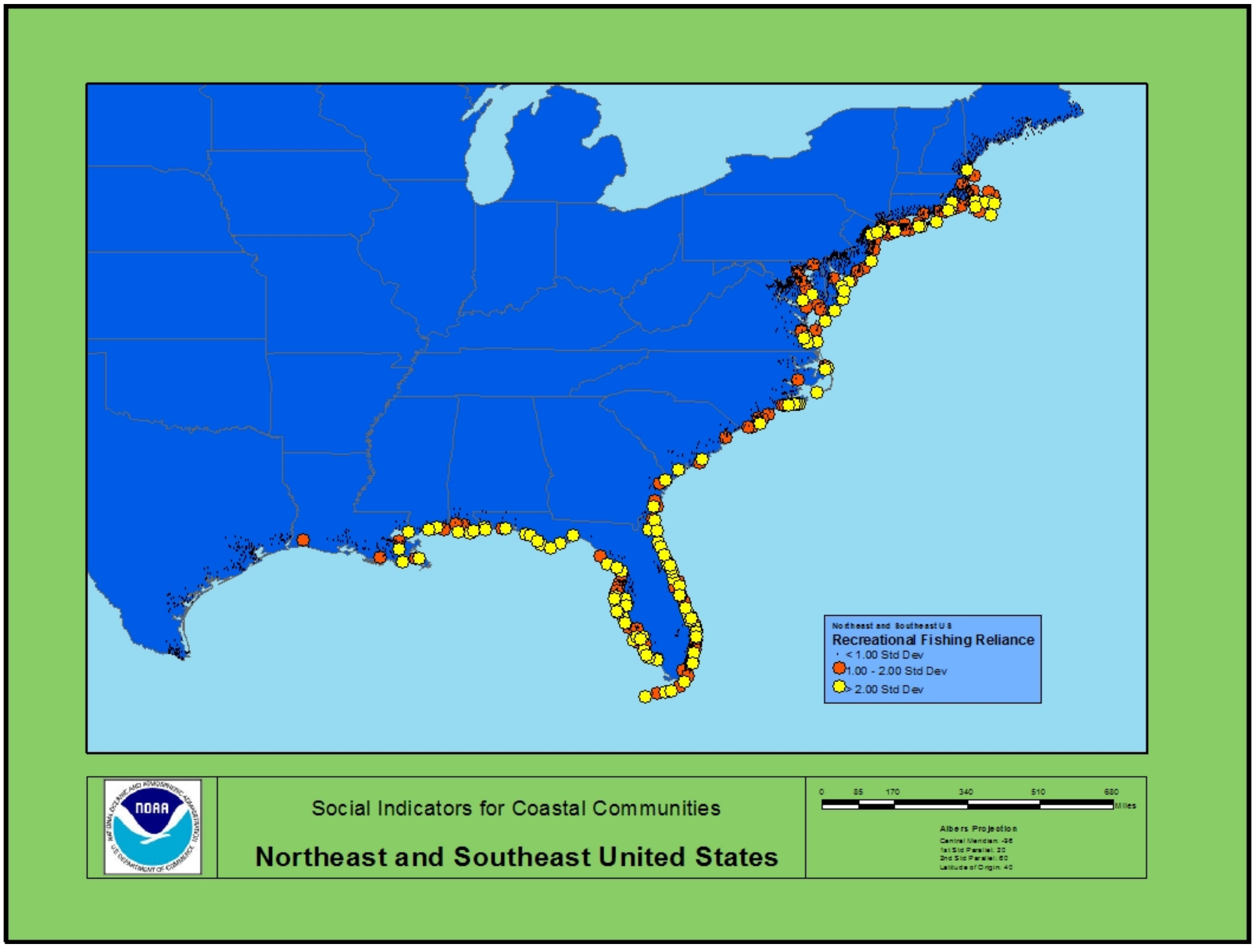

Figure A-10. Recreational Fishing Reliance Index.

Table A-11 Recreational Fishing Engagement Index.

Community	Recreational charter fishing pressure	Recreational private fishing pressure	Recreational shore fishing pressure	Recreational Engagement Index Score
Virginia Beach, VA (18)	15,167.7	47,758.3	43,297.5	**10.841**
Ocean City, MD (14))	30,495.7	12,487.7	21,580.5	**6.856**
Marathon, FL (14)	13,739.9	35,049.6	9,411.3	**5.641**
Orange Beach, AL (20)	33,812.6	12,747.7	7,106.1	**5.626**
Point Judith, RI (22)	14,288.1	8,477.5	26,526.6	**5.153**
Barnegat Light, NJ (22)	16,357.1	13,430.1	7,561.1	**3.709**
Biloxi, MS (14)	8,330.2	11,579.9	12,201.7	**3.126**
St. Marks, FL (33)	4,432.7	26,494.1	3,570.4	**3.093**
Seabrook, NH (25)	17,024.4	3,581.2	3,849.9	**2.442**
Gulfport, MS (13)	0.0	7,951.1	10,901.8	**1.668**
Newport, RI (21)	574.1	3,286.6	9,666.9	**1.157**
Wanchese, NC (32)	6,436.7	5,628.6	0.0	**0.964**
New Bedford, MA (34)	1,698.5	2,448.1	4,053.5	0.573
Cameron, LA (32)	0.0	3,228.1	1,200.2	0.125
Bayou La Batre, AL (32)	0.0	2,001.8	1,447.2	0.038
Stonington, ME (10)	0.0	0.0	151.7	-0.297
Houma, LA (10)	0.0	0.0	0.0	-0.314
Cushing, ME (4)	0.0	0.0	0.0	-0.314
Port Aransas, TX (25)	0.0	0.0	0.0	-0.314
Port Arthur, TX (4)	0.0	0.0	0.0	-0.314
Factor Loading	**0.352**	**0.815**	**0.761**	
Percentage Explained Variation	**63.02**	Index scores in bold are at or above threshold of one standard deviation if rounded.		
Theta Reliability	**0.768**			
Eigenvalue	**2.045**			

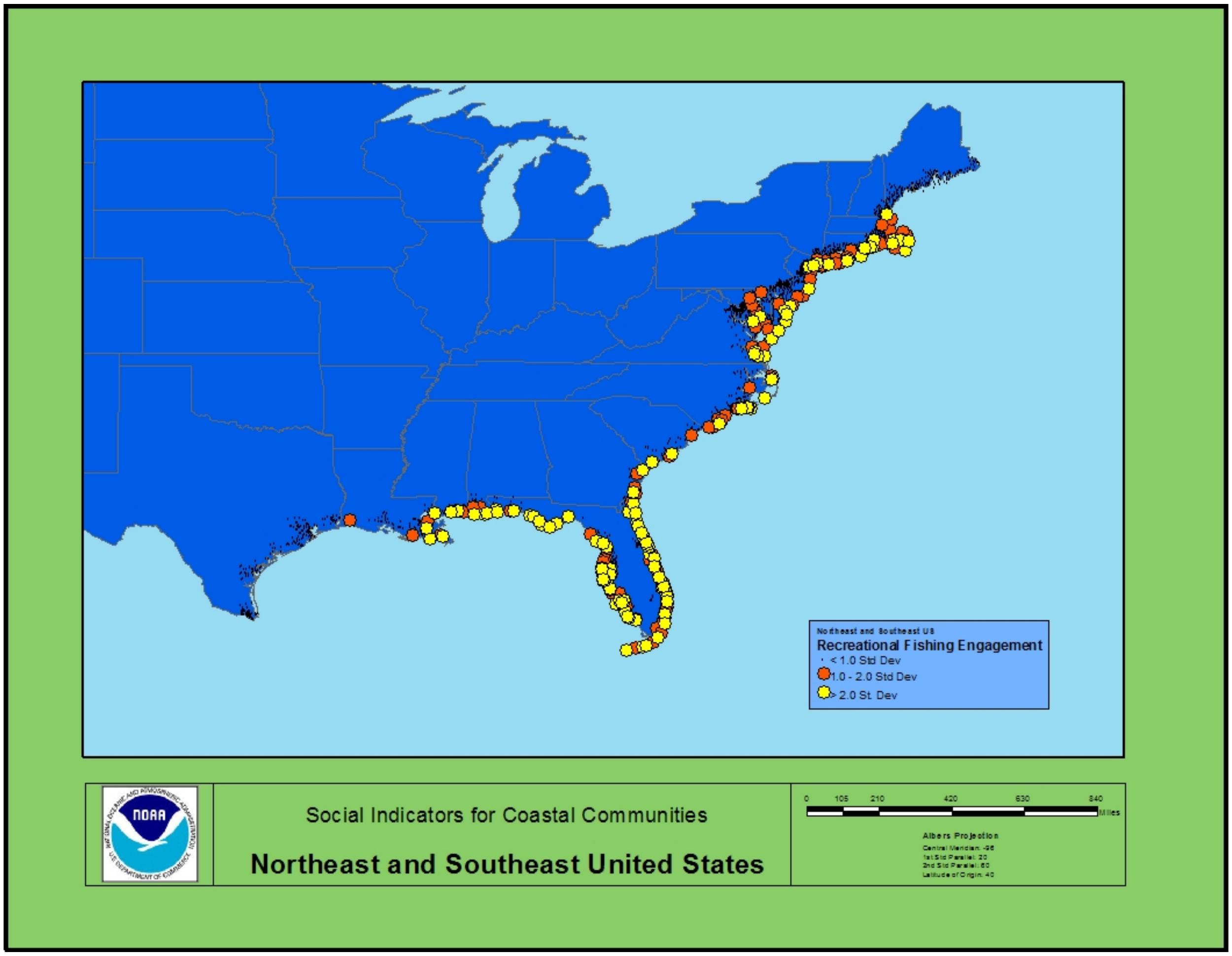

Figure A-11. Recreational Fishing Engagement Index.

Table A-12. Commercial Fishing Reliance Index

Community	Value of landings by population	Number of commercial permits by population	Number of dealers with landings by population	Percent in agriculture, forestry and fishing	Commercial Reliance Index Score
Stonington, ME (10)	46,442,040.0	108.7	7.2	44.1	**14.785**
Cameron, LA (32)	12,086,479.0	40.4	24.5	7.6	**6.701**
St. Marks, FL (33)	5,649,861.0	110.6	19.2	5.0	**5.494**
Barnegat Light, NJ (22)	7,337,200.0	181.8	1.2	7.7	**4.525**
Bayou La Batre, AL (32)	11,447,615.0	48.8	7.1	9.5	**4.387**
Wanchese, NC (32)	10,081,620.0	42.2	5.9	11.6	**4.020**
Cushing, ME (4)	*	34.3	0.7	9.5	**1.771**
Point Judith, RI (22)	1,921,666.0	93.9	0.7	1.4	**1.642**
New Bedford, MA (34)	3,327,873.0	41.4	0.3	0.9	**1.084**
Houma, LA (10)	270,150.0	0.6	0.8	11.2	0.728
Ocean City, MD (14))	*	40.1	0.3	0.0	0.579
Marathon, FL (14)	1,006,345.0	8.4	1.4	4.4	0.565
Port Aransas, TX (25)	73,373.0	1.9	2.4	5.4	0.496
Seabrook, NH (25)	*	27.1	0.1	0.3	0.191
Port Arthur, TX (4)	714,330.0	0.7	0.2	1.6	0.008
Newport, RI (21)	280,046.0	12.2	0.3	0.2	0.001
Orange Beach, AL (20)	*	2.2	0.2	2.9	-0.012
Biloxi, MS (14)	361,776.0	2.1	0.2	0.8	-0.099
Virginia Beach, VA (18)	*	0.4	0.0	0.4	-0.249
Gulfport, MS (13)	0.0	0.2	0.0	0.4	-0.253
Factor Loading	**0.833**	**0.686**	**0.592**	**0.705**	
Percentage Explained Variation	**50.03**	Index scores in bold are at or above threshold of one standard deviation if rounded. * Data suppressed for confidentiality purposes			
Theta Reliability	**0.664**				
Eigenvalue	**1.995**				

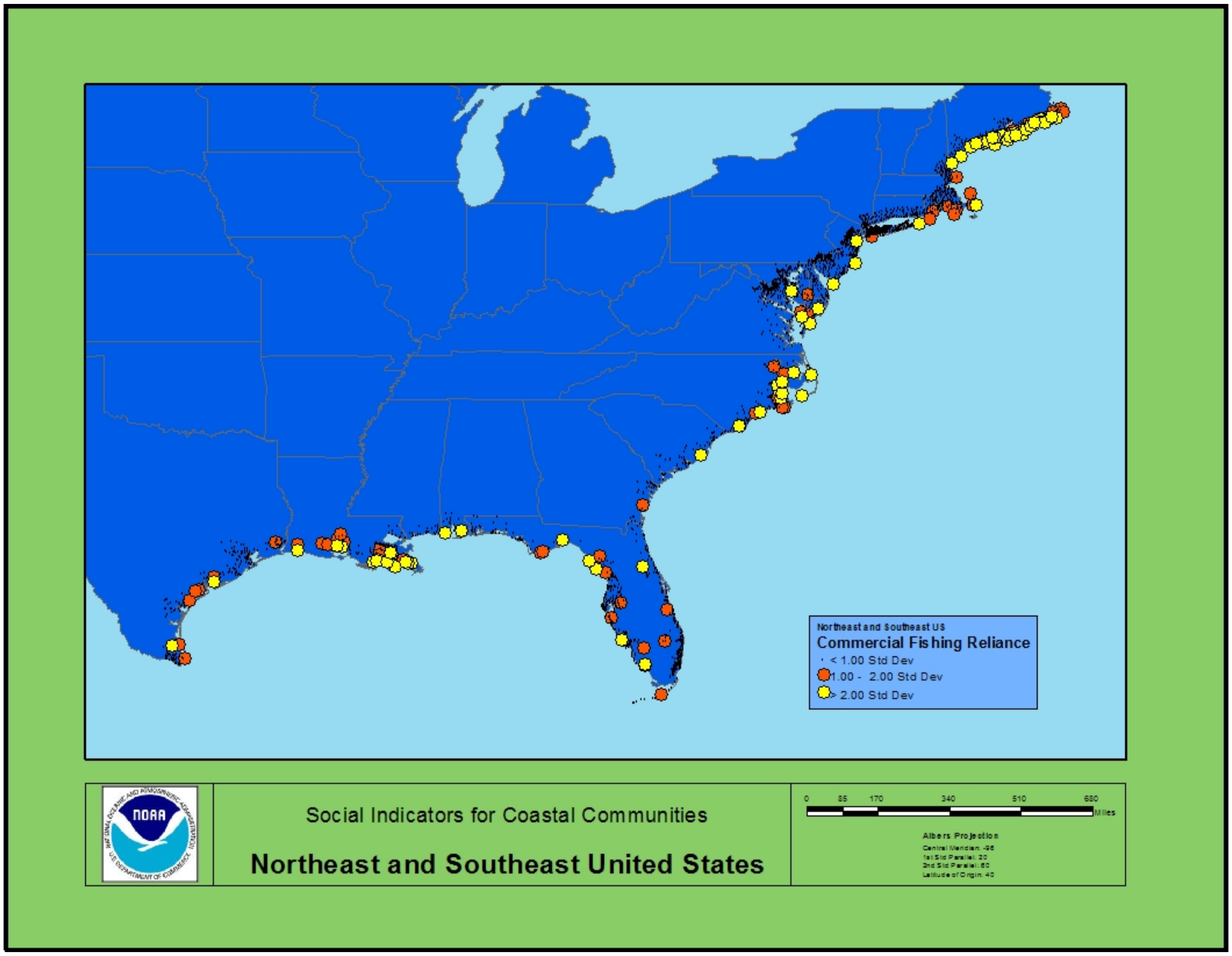

Figure A-12. Commercial Fishing Reliance Index.

Table A-13. Commercial Fishing Engagement Index

Community	Value of landings	Number of commercial permits	Number of dealers with landings	Pounds of Landings	Commercial Engagement Index Score
New Bedford, MA (34)	303,964,574.0	3,785.0	31.0	125,049,839.0	**36.953**
Point Judith, RI (22)	31,857,371.0	1,557.0	11.0	33,363,620.0	**8.807**
Cameron, LA (32)	8,375,930.0	28.0	17.0	167,109,618.0	**6.519**
Barnegat Light, NJ (22)	25,782,922.0	745.0	5.0	12,547,401.0	**4.480**
Bayou La Batre, AL (32)	32,373,854.0	138.0	20.0	6,946,891.0	**4.278**
Stonington, ME (10)	45,280,989.0	106.0	7.0	16,137,402.0	**3.951**
Port Arthur, TX (4)	39,742,480.0	38.0	9.0	16,976,794.0	**3.484**
Houma, LA (10)	8,799,330.0	21.0	26.0	14,848,297.0	**2.589**
Wanchese, NC (32)	15,283,736.0	64.0	9.0	4,110,964.0	**2.117**
Biloxi, MS (14)	16,970,532.0	99.0	8.0	15,730,345.0	**2.052**
Newport, RI (21)	6,786,625.0	295.0	7.0	7,141,975.0	**1.979**
Ocean City, MD (14))	*	282.0	2.0	*	**1.925**
Marathon, FL (14)	9,758,531.0	81.0	14.0	2,240,007.0	**1.850**
Seabrook, NH (25)	*	230.0	1.0	*	0.849
Port Aransas, TX (25)	276,688.0	7.0	9.0	67,693.0	0.572
Virginia Beach, VA (18)	*	177.0	1.0	*	0.544
Cushing, ME (4)	*	48.0	1.0	*	0.427
St. Marks, FL (33)	1,175,171.0	23.0	4.0	463,453.0	0.297
Orange Beach, AL (20)	*	13.0	1.0	*	-0.057
Gulfport, MS (13)	0.0	11.0	0.0	0.0	-0.142
Factor Loading	**0.906**	**0.862**	**0.580**	**0.635**	
Percentage Explained Variation	**57.57**	Index scores in bold are at or above threshold of one standard deviation if rounded. * Data suppressed for confidentiality purposes			
Theta Reliability	**0.750**				
Eigenvalue	**2.294**				

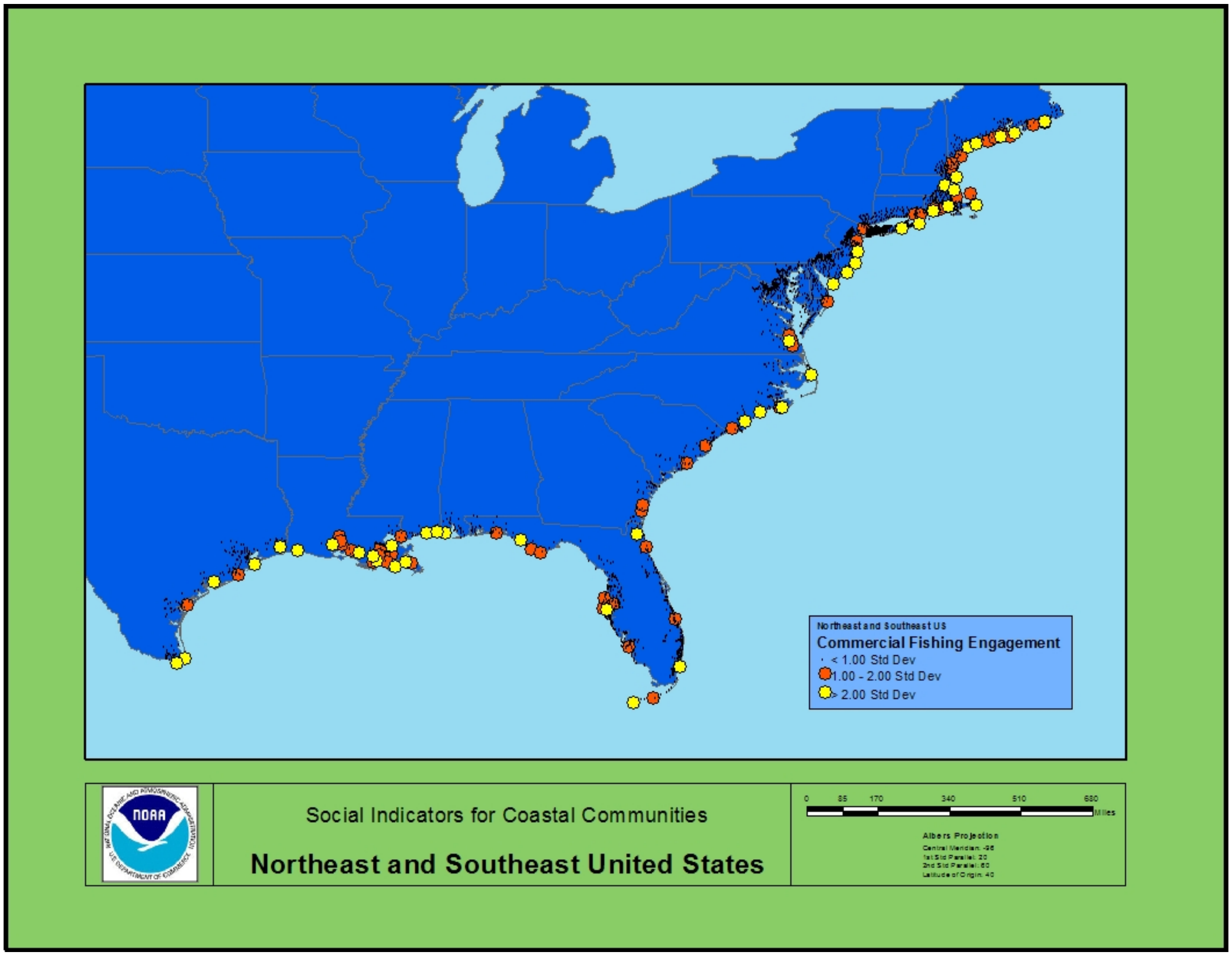

Figure A-13. Commercial Fishing Engagement Index.

Appendix 2. Variable Codebook

Variable name	Variable Description	Data source
GEO_ID	Geography Identifier	Census ACS Summary File
GEO_ID2	Geography Identifier	Census ACS Summary File
SUMLEVEL	Geographic Summary Level	Census ACS Summary File
GEO_NAME	Community Name	Census ACS Summary File
TOTPOP	Total estimated Population	Census ACS Demographic Summary File C0
PCTMALES	Percent Males	Census ACS Demographic Summary File C6
PCTFEMALE	Percent Females	Census ACS Demographic Summary File C10
POPCHPCT	Pop Change (per cent)	Census ACS Demographic Summary File C0 minus 2000 Population Divided by 2000 Population
POPDENS	Population Density	Census ACS Demographic Summary File C0 Divided by Area in sq miles
POP0_5PCT	Population age under 5	Census ACS Demographic Summary File C14
POP85PCT	Population 85 plus	Census ACS Demographic Summary File C62
MEDAGE	Median Age	Census ACS Demographic Summary File C64
POPWAPCT	Percent White Alone population	Census ACS Demographic Summary File C125
POPBAPCT	Percent Black Alone population	Census ACS Demographic Summary File C129
POPNAPCT	Percent Native Americans Alone population	Census ACS Demographic Summary File C133
POPAAPCT	Percent Asian Alone population	Census ACS Demographic Summary File C153
POPPAPCT	Percent Pacific Alone population	Census ACS Demographic Summary File C185
POPHSPCT	Percent Hispanic population	Census ACS Demographic Summary File C257
POPWNPCT	Percent White non-Hispanic population	Census ACS Demographic Summary File C285
TOTHU	Total Housing Units	Census ACS Housing Summary File C0
PCTVACANT	Percent Vacant Housing Units	Census ACS Housing Summary File C10
HMOWNVAC	Homeowner Vacancy Rate	Census ACS Housing Summary File C12
RENTVAC	Rental Vacancy Rate	Census ACS Housing Summary File C15
PCTMBLHM	Percent Mobile Homes	Census ACS Housing Summary File C52
PCTBLT2005	Proportion Built 2005 or later	Census ACS Housing Summary File C64
PCTBLT2000	Proportion Built 2000-2004	Census ACS Housing Summary File C66
HUMNR	Median number of rooms	Census ACS Housing Summary File C138
PCTOWNER	Percent Owner	Census ACS Housing Summary File C175
PCTRENTER	Percent Renter	Census ACS Housing Summary File C179
MOV2005	Moved in 2005 or later	Census ACS Housing Summary File C193
MOV2000TO04	Moved in 2000 to 2004	Census ACS Housing Summary File C197
PCTNOVHCL	Households w/o transportation vehicles	Census ACS Housing Summary File C221
HOUSHEATFUEL	Percent of households heating with fuel oil	Census ACS Housing Summary File C253
PCTNOPLBG	Households w/o plumbing facilities	Census ACS Housing Summary File C281
MEDHOMVAL	Median Home Value	Census ACS Housing Summary File C343
MED_MTMRG	Median mortgage, monthly payment	Census ACS Housing Summary File C390
OWNRMTHLYCST	Percent of households with monthly owner costs 35.0 percent or more of household income	Census ACS Housing Summary File C442
MED_GRRNT	Median gross rent	Census ACS Housing Summary File C514
RENTRMTHLYCST	Percent of households with monthly renter costs 35.0 percent or more of household	Census ACS Housing Summary File C546

	income	
TOTHH	Total estimated Households	Census ACS Social Summary File C0
PCTHFOFMNOHS	2+ persons HH, other family HH, female HHldr, no husband	Census ACS Social Summary File C30
PCTHHUNDR18	Households w one or more under 18	Census ACS Social Summary File C50
PCTHHUOVER65	Households w one or more over 65	Census ACS Social Summary File C54
AVGHHSZE	Average HH Size	Census ACS Social Summary File C56
PCTMALESEPARATD	Percentage males separated	Census ACS Social Summary File C104
PCTMALEDIVORCD	Percentage males divorced	Census ACS Social Summary File C112
PCTFEMALESEPARATD	Percentage females separated	Census ACS Social Summary File C128
PCTFEMALEDIVORCD	Percentage females divorced	Census ACS Social Summary File C136
PCTPOP9THGRD	Less than 9th grade	Census ACS Social Summary File C227
PCTNODIPLOMA	9th to 12th no diploma	Census ACS Social Summary File C231
PCTPOPHSGRD	High school grad	Census ACS Social Summary File C235
PCTBATCHLRS	Bachelor's degree	Census ACS Social Summary File C247
PCTLIVESMHS	Lived in same house 1 yr ago	Census ACS Social Summary File C289
PCTLIVEDFCO	Lived in different county	Census ACS Social Summary File C301
PCTLIVDFST	Lived in different state	Census ACS Social Summary File C309
PCTFORBRN	Percent foreign born	Census ACS Social Summary File C341
PCTSPKENGNTWL	Percent speak English less than very well	Census ACS Social Summary File C425
PCTLABFORCE	Percent Labor force	Census ACS Economic Summary File C6
PCTEMPLOYED	Percent Employed	Census ACS Economic Summary File C14
PCTUNEMPLD	Percent Unemployed	Census ACS Economic Summary File C18
PCTLABFEMALE	Percent females in Labor force	Census ACS Economic Summary File C45
PCTEMPFEMA	Percent females employed	Census ACS Economic Summary File C49
MEANTRAVTIM	Mean travel time to work	Census ACS Economic Summary File C95
PCTSERVOCC	Service occupations	Census ACS Economic Summary File C108
PCTFRMFSHOCC	Farm, fishing and forestry occupations	Census ACS Economic Summary File C116
PCTAGRFRFSH	Agriculture, forestry, fishing, and hunting industry	Census ACS Economic Summary File C132
PCTSERVIND	Arts, Entertainment and recreation industry	Census ACS Economic Summary File C172
PCTSLFEMP	Percent of Class of Worker Self Employed	Census ACS Economic Summary File C197
PCTHHHUNDR10K	Households w/ income under $10,000	Census ACS Economic Summary File C208
PCTHH200K	HH w/ income $200,000+	Census ACS Economic Summary File C244
MEDHHINC	Median HH income	Census ACS Economic Summary File C246
MEANHHINC	Mean HH income	Census ACS Economic Summary File C249
PCTRECSOC	Percent people receiving Social Security	Census ACS Economic Summary File C261
PCTRECRET	Percent with Retirement income	Census ACS Economic Summary File C268
MEANRETINC	Mean Retirement income	Census ACS Economic Summary File C270
PCTRECSSI	Percent people receiving SSI	Census ACS Economic Summary File C275
PUBLICASSIST	Percent households with cash public assistance income	Census ACS Economic Summary File C282
PERCPHHINC	Per Capita Income	Census ACS Economic Summary File C341
PCFMINPOV	Per cent of families below poverty level	Census ACS Economic Summary File C377
PCTPOV	Percentage population in poverty	Census ACS Economic Summary File C404
PCTCHLDPOV	Percentage under 18 in poverty	Census ACS Economic Summary File C407
PCT65POV	Percentage 65 and over in poverty	Census ACS Economic Summary File C425
PCTCHGRNT	Percentage change median rent	Census ACS data Summary File and Census 2000 Data

	2000-2010	
PCTCHGMRG	Percentage change median mortgage 2000-2010	Census ACS data Summary File and Census 2000 Data
PCTCHNGHOMVAL	Percentage change in property values 2000-2010	Census ACS data Summary File and Census 2000 Data
PCTCHGRENTER	Percent change in # of renters 2000-2010	Census ACS data Summary File and Census 2000 Data
PCTCHGUNEM	Percentage change in unemployment 2000-2010	Census ACS data Summary File and Census 2000 Data
PCTCHGRAVTIM	Percentage change travel time to work 2000-2010	Census ACS data Summary File and Census 2000 Data
MEDDWELLAGE	Median dwelling age	Census ACS data Detailed Tables B25035_1_EST
MDYRSRESID	Median years in residence	Census ACS data Detailed Tables B25039_1_EST
HASMORTGAGE	Percent of housing units with a mortgage	Census ACS Detailed Tables B25081_1_EST
HSMORTGAGELON	Percent of housing units with a mortgate and both second mortgage and home equity loan	Census ACS Detailed Tables B25081_2_EST
PCTGRPQRTRS	Percent living in group quarters	Census ACS Detailed Tables B25081_6_EST
GININDEX	Gini Index	Census ACS Detailed Tables B19083_6_EST
SHNNINDEX	Shannon Index	Calculated With ACS Census Economic Summary File
PCTWTRCVRG	Percent Water-cover	Census Tiger Files Places Shape Files
MARINANUM	Number of Marinas in County	Census Business Patters
EPAREGFAC	EPA Registered facilities	EPA http://www.epa.gov/enviro/
NUMBOTRMPS	Boat Launches per population	MRIP Site Survey
NEARCTYPOP	Nearest city w/ 50k pop in miles	Neighborhood guides (www.moving.com)
CSTOFLIVNG	Cost of living index 2010	CLResearch Website (http://www.clrsearch.com)
CRIMINDEX	Total Crime Index	CLResearch Website (http://www.clrsearch.com)
HAILRSKAVG	Damaging Hail Risk Average	Neighborhood guides (www.moving.com)
HURRSKAVG	Damaging Hurricanes Risk Average	Neighborhood guides (www.moving.com)
TORNRSKAVG	Damaging Tornadoes Risk Average	Neighborhood guides (www.moving.com)
WNDRSKAVG	Damaging Winds Risk Average	Neighborhood guides (www.moving.com)
POUNDS	Pounds of Landings	Regional NOAA Fisheries
PNDSPRPOP	Pounds of Landings per 1,000 persons	Regional NOAA Fisheries
VALUE	Value of Landings	Regional NOAA Fisheries
VALUPRPOP	Value of Landings Per population	Regional NOAA Fisheries
COMMPMT	Number of Commercial Permits	Regional NOAA Fisheries
COMMPRPOP	Commercial Fishing Permits per population	Regional NOAA Fisheries
CHARTERPMT	Number of Charter Permits	Regional NOAA Fisheries
CHARTERPMTPOP	Charter Permits per population	Regional NOAA Fisheries
DEALERNUM	Number of Dealers	Regional NOAA Fisheries
DEALERNUMPOP	Dealers with Landings per population	Regional NOAA Fisheries
RECPSSRMODEALL	Recreational fishing pressure estimate all modes combined	MRIP Site Survey
RECMODEALLPOP	Recreational fishing pressure estimate all modes by population	
RECPSSRMODECH	Recreational fishing pressure estimate charter mode	MRIP Site Survey

RECMODECHRPOP	Recreational fishing pressure estimate charter mode by population	
RECPSSRMODEPR	Recreational fishing pressure estimate private recreational mode	MRIP Site Survey
RECMODEPRPOP	Recreational fishing pressure estimate private recreational mode by population	
RECPSSRMODESH	Recreational fishing pressure estimate shore mode	MRIP Site Survey
RECMODESHRPOP	Recreational fishing pressure estimate shore mode by population	
PRIMARY_LATITUDE	Latitude	USGS State and Topical Gazetteer Download Files
PRIMARY_LONGITUDE	Longitude	USGS State and Topical Gazetteer Download Files

Appendix 3. Index Calculation and Formulas

Shannon Index

The Shannon index is a diversity index that is often used in the ecological literature. It has numerous other titles such as Shannon's diversity index, the Shannon-Wiener index, the Shannon-Weaver index, the Shannon-Weiner index and the Shannon entropy. The idea is that the more different species (or in this case occupations) there are, and the more equal their proportional abundances, the more species diversity exists within the ecosystem. Therefore, the presumption is the closer to zero the Shannon index score, the less diversity. In fact, if only one species (or occupation) exists within the ecosystem then the Shannon index equals zero.

The calculation used all occupations for each state's coastal communities. So, the index score is calculated on a state by state basis, using only those coastal communities in each state included in the research.

Calculation for the Shannon Index of Occupational Diversity:

$$H = \sum_{i=1}^{s} - (P_i * \mathit{ln}\, P_i)$$

where:
H = the Shannon occupational diversity index
P_i = fraction of the entire population made up of occupation i
S = number of occupation categories encountered
$\sum$ = sum from occupation 1 to occupation S

SPSS Syntax for calculating the Shannon Index from Census Occupational data percentages.

```
DATASET ACTIVATE DataSet1.
COMPUTE Logmanag=LG(ManagePct).
EXECUTE.
COMPUTE Logsrvice=LG (SrvicePct).
EXECUTE.
COMPUTE Logsales=LG(SalesPct).
EXECUTE.
COMPUTE Logfrmfsh=LG10(FrmfshPct).
EXECUTE.
COMPUTE Logcnstrct=LG(CnstrctnPct).
EXECUTE.
COMPUTE Logprodctn=LG(ProdctnPct).
EXECUTE.
RECODE Logmanag Logsales Logsrvice Logfrmfsh Logcnstrct Logprodctn (SYSMIS=0.00).
EXECUTE.
COMPUTE Managpctlog=ManagePct * Logmanag.
EXECUTE.
COMPUTE Srvicepctlog=SrvicePct * Logsrvice.
```

```
EXECUTE.
COMPUTE Salespctlog=SalesPct * Logsales.
EXECUTE.
COMPUTE Frmfshpctlog=FrmfshPct * Logfrmfsh.
EXECUTE.
COMPUTE Cnstrctnpctlog=CnstrctnPct * Logcnstrct.
EXECUTE.
COMPUTE Prodctnpctlog=ProdctnPct * Logprodctn.
EXECUTE.
COMPUTE Indexcalc=Managpctlog + Srvicepctlog + Salespctlog + Frmfshpctlog +
Cnstrctnpctlog + Prodctnpctlog.
EXECUTE.
COMPUTE Shannonindx=Indexcalc * -1.
EXECUTE.
```

Theta Reliability Calculation

Theta reliability was hand calculated using the following formula:

$\theta = [\rho / (\rho - 1)] \times [1 - (1/\lambda)]$
ρ = # scale items
λ = largest eigenvalue