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Understanding Resilience in Communities Across the U.S. Coastline

Indicators, Pressures, and Applications

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For more information, please visit:
https://coastalscience.noaa.gov/project/programmatic-execution-of-nccos-vulnerability-assessments/

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Understanding Resilience in Communities Across the U.S. Coastline

Indicators, Pressures, and Applications

Prepared by

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Acronyms

ACS	American Community Survey
ARRA	American Recovery and Reinvestment Act of 2009
BRIC	Baseline Resilience Indicators for Communities
CEQ	White House Council on Environmental Quality
CIRI	Community Intrinsic Resilience Index
CRE	Community Resilience Estimates
CRSI	Cumulative Resilience Screening Index
DROP	Disaster Resilience of Place
HIFLD	Homeland Infrastructure Foundation-Level Data
HVRI	Hazards and Vulnerability Research Institute
MRV	Measuring Resilience and Vulnerability
NCCOS	National Centers for Coastal Ocean Science
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
OCM	Office for Coastal Management
PDD	Presidentially Declared Disaster
PEOPLES	Population and Demographics, Environmental and Ecosystem, Organized Governmental Services, Physical Infrastructures, Lifestyle and Community Competence, Economic Development, and Social-Cultural Capital
RCDB	Restoration and Conservation Database
REDI	Resilience to Emergencies and Disasters Index
RIM	Resilience Interference Measurement
SHELDUS	Spatial Hazard Events and Losses Database for the United States
SOVI	Social Vulnerability Index
TBRIC	Tract-level Baseline Resilience Indicators for Communities

Executive Summary

This report presents an exploratory study of resilience within coastal communities across the U.S. Researchers at the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Coastal Ocean Science (NCCOS) have implemented a portfolio of work that historically assesses the intersection between coastal hazards and vulnerability in coastal communities. The study described within this report aims to expand this portfolio of work to include resilience concepts by exploring the varied definitions and approaches to quantifying resilience within a hazard preparedness and response context. The findings from this work may enable NOAA researchers to implement future studies of community resilience and better target place-based studies. Further, this type of work could support NOAA granting offices in better targeting restoration investments.

The goals of this study were to: 1) identify a quantitative approach to measuring resilience in coastal communities, 2) analyze patterns of resilience, and 3) understand how patterns of resilience relate to investments in restoration and disaster recovery. From a collection of nine frameworks that met the study needs, two resilience frameworks–the Baseline Resilience Indicators for Communities (BRIC; Cutter et al., 2014) and Cumulative Resilience Screening Index (CRSI; Summers et al., 2020)–were chosen for the focus of this study. Each framework was replicated for this nationwide study of U.S. coastal shoreline counties as they each use secondarily sourced datasets that can help expedite the process of identifying communities in need of increased resilience. Additionally, the relationship between resilience metrics, presidentially declared disasters, and restoration investments was explored.

Resilience index values varied by the index used; this was expected due to a difference in the indicators included in each framework and different operating definitions of resilience. The biggest difference between BRIC and CRSI is that CRSI includes additional thematic areas in the form of domains addressing risk and governance. The two indices told a similar story with the metrics that relied on similar data, such as those related to social domains. However, the indices told different stories with regard to their overall total resilience scores because the domains that differed had heavy influence on the overall score and introduced sometimes opposing dynamics based on varying definitions of resilience. The resilience indices, however, told a consistent story when compared to where disasters occur and restoration money is invested. Counties with high built infrastructure and housing domain scores in either index tended to have higher resilience scores overall.

This comparison and use of existing resilience indices are a first, relatively simple, step in NOAA's study of resilience before delving into more in-depth methodologies that require investment from community members. The goal is to quantitatively characterize resilience in coastal communities across the country, efficiently. Moving forward, as data management practices change and new indicators may become available, each indicator's construction can be reconsidered. The increased complexity of many resilience frameworks does bring added power to a secondarily sourced, indicator-based analysis, both statistically and in the ability to address more concepts. Additionally, some measures of resilience could be incorporated into the Vulnerability Assessment Portfolio's existing methodologies alongside similar concepts in their thematic domain. Not all resilience and vulnerability measures can be utilized this way, however, and future assessments should not assume that highly resilient communities are not vulnerable (and vice versa).

Chapter 1: Introduction

Hazard exposure in coastal communities across the U.S. is increasing as urban development and populations along the coastline continue to expand and climate effects become more prevalent. As such, a comprehensive understanding of the inherent conditions and characteristics of a community prior to a major impact is essential to achieving effectual coastal protection and management. In recent years, researchers at the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Coastal Ocean Science (NCCOS) have implemented a portfolio of work that assesses the intersection between coastal hazards and vulnerability in coastal communities (Fleming et al., 2017; Fleming et al., 2022; Messick et al., 2016). The study described within this report aims to supplement this portfolio of work by exploring the varied definitions and approaches to quantifying resilience within a hazard preparedness and response context.

The NOAA National Ocean Service (2024) defines coastal resilience as "the ability of populations, ecosystems, and economies to prepare for, absorb, respond to, recover from, and successfully adapt to the impacts of natural and human-caused hazards, such as hurricanes and oil spills, and long-term environmental change, such as habitat loss and sea level rise." Vulnerability is defined as the "propensity or predisposition of assets to be adversely affected by hazards" (U.S. Climate Resilience Toolkit, 2021). While vulnerability and resilience can therefore sometimes be interpreted as antonyms (Adger, 2000, 2006), measures of both are needed to accurately interpret community capacity and dynamics (Derakhshan et al., 2022a). A community's inherent resilience, therefore, cannot solely be defined by or measured as the inverse of its inherent vulnerabilities (Cutter et al., 2008). Vulnerability and resilience can certainly share overlapping or indirectly related metrics, but they are distinct concepts whose relationship can vary depending on the theoretical, spatial, or temporal application (Cutter et al., 2014; Cutter, 2016a; Derakhshan et al., 2022a). These are far from settled terms, however, and different researchers use the terms in vastly different ways according to context, need, and related stakeholder power dynamics (Cretney 2014; Cutter, 2016b). The human dimensions of vulnerability and resilience are not always considered in resilience research and adaptation planning (Loerzel and Dillard, 2021), and how any of these concepts interact with risk varies.

Community resilience is predicated on its assets that can withstand an impact and support the process of recovery and adaptation (Berkes and Ross, 2016). Assets that contribute to a community's resilience may include social and political systems, infrastructure, environmental resources, and even a community's collective experience (Cardoni et al., 2021; Cimellaro et al., 2016; Cutter et al., 2014; De Iuliis et al., 2022; Gerges et al., 2022; Kontokosta and Malik, 2018; Lam et al., 2016; Loerzel and Dillard, 2021; Miller et al., 2016; Renschler et al., 2010; Summers et al., 2022). As exemplified by Cutter et al. (2014) and Derakhshan et al. (2022a), a socially vulnerable community may feasibly be resilient in some capacity, depending on the resources available that can enable preparedness for, absorption of, recovery from, and adaptation to an impact. The availability of these resources can be highly variable across regions and time scales, often depending on a system of connected processes (e.g., governance, organization, social networks) within a community that contributes to the adaptive cycle (Brown, 2014; Berkes and Ross, 2016). The measurement of both vulnerability and resilience, especially across space and time, can expand coastal managers' and decision-makers' understanding of a community's capacity to withstand future stresses.

NOAA researchers can better target place-based studies, and NOAA granting offices can better target restoration investments in locations in need of increased resilience by recognizing these distinct aspects of resilience and identifying a mechanism for quantifying them. These types of place-based studies can also support a community in qualifying for adaptation funding, such as that provided via the Infrastructure Investment and Jobs Act (2021). Such studies offer required baseline data and documentation of need. It is important to establish a baseline understanding of a community's resilience without placing a burden on overextended local stakeholders before any resources are distributed. As such, making use of existing datasets to assess resilience using robust, valid, and reliable frameworks can expedite the process of identifying communities in need, especially those identified as disadvantaged or underserved. The goals of this study were to:

1) identify a quantitative approach to measuring resilience in coastal communities
2) analyze patterns of resilience
3) understand how patterns of resilience relate to investments in restoration and disaster recovery

Chapter 2: Methods

2.1 Study Parameters

2.1.1. Study Area

This national-scale study encompasses U.S. coastal shoreline counties as defined by the NOAA Office for Coastal Management (OCM) Digital Coast (NOAA OCM, 2010), including Alaska and Hawaii but excluding U.S. territories. This definition of coastal counties was chosen to maintain consistency with other NOAA data products and identifies 397 coastal shoreline counties that are directly adjacent to the open ocean, major estuaries, and the Great Lakes (Figure 1). NOAA OCM states that coastal counties, “due to their proximity to these waters, bear a great proportion of the full range of effects from coastal hazards and host the majority of economic production associated with coastal and ocean resources.” Excluding Alaska, U.S. coastal counties cover only 10% of the land mass yet are home to almost 40% of the total population (NOAA OCM, 2023).

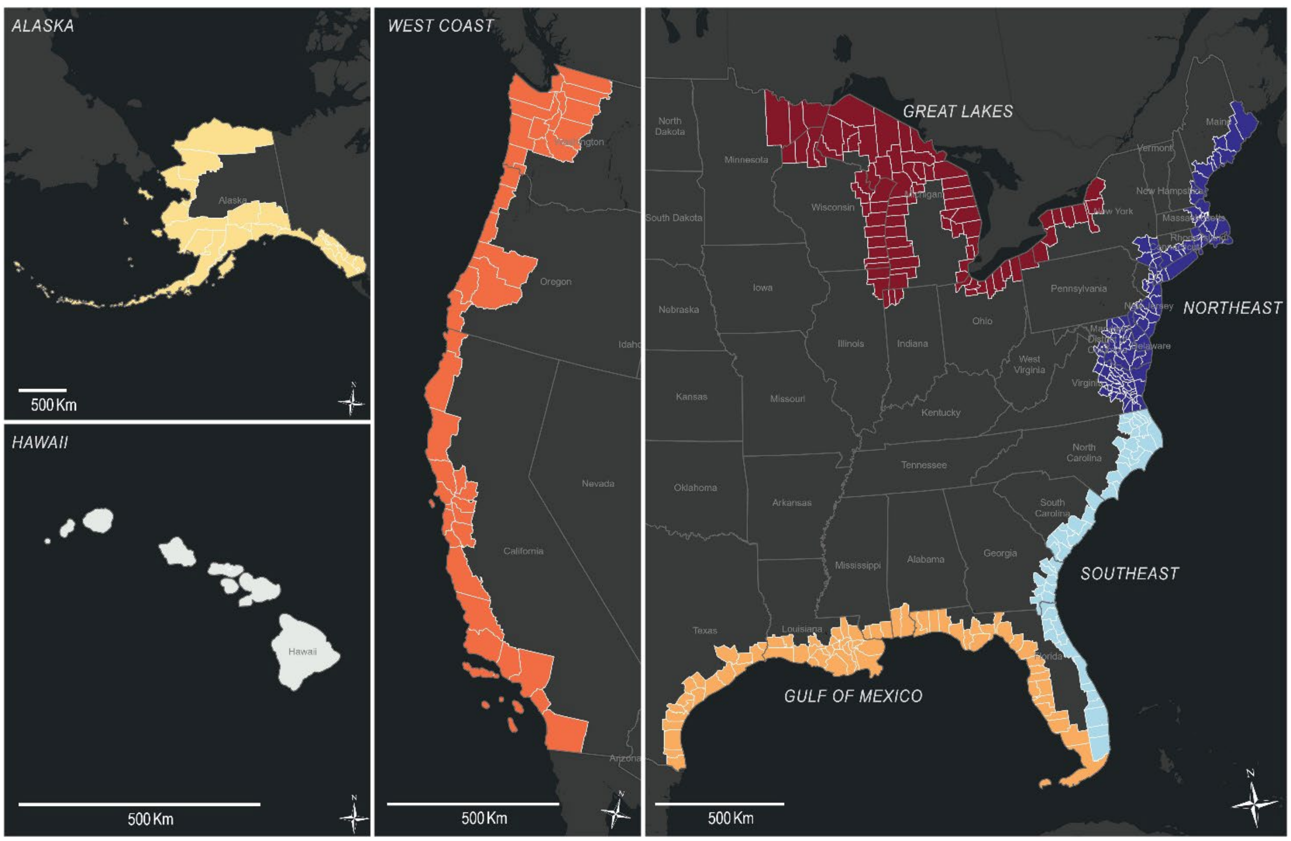


Figure 1. Map of the study area, which includes all coastal shoreline counties within the conterminous U.S., Alaska, and Hawaii. Each county was assigned to one of seven regions, indicated by different colors on the map.

2.1.2 Units of Analysis

This work is an exploratory study of potential approaches to measuring resilience and a screening tool for future, scaled-down, place-based analyses that require closer collaboration with local partners. While metrics of resilience could be calculated at a wide range of spatial scales, a county-level analysis was chosen for this study because data availability, especially of human dimensions data (e.g., economic and health metrics), is often at the county or larger scale. Additionally, there are enough counties to compare statistically between geographies. While this county-level analysis may mask more localized community-scale dynamics, it enables a multifaceted, data-rich analysis of resilience metrics.

This study was originally designed to measure resilience at decennial increments from 2000 to 2020, matching the decennial U.S. Census. However, data availability from the year 2000 was limited (e.g., databases for several major data providers only archive data starting around 2010 due to advances in data storage technology). For 2010, a large number of measures (e.g., quantified individual values or data inputs) were unavailable or would have to be reconceptualized. For example, the number of nuclear power plants (a risk factor in the Cumulative Resilience Screening Index [CRSI]) is fairly stable over time, and a new plant coming online or one being taken offline is so unusual that the database can be kept up to date in real time; archives, however, are not maintained. Because of these types of limitations, comparisons across time are limited to certain measures and/or groups of measures, depending on accessibility and replicability.

Further, many data providers caution against deriving comparisons and analyses from certain datasets over time as methodologies (such as survey design, implementation, or estimation procedures) may differ or, specific to the U.S. Census Bureau, geographical boundaries may change (U.S. Census Bureau, 2024). Therefore, while resilience is typically defined as the ability to bounce back from disturbance (therefore requiring a temporal analysis), the frameworks discussed here instead measure the *capacity* for resilience (in other words, having the required resources to recover). Therefore, temporal analyses were not entirely possible or necessary, and indices calculated for the year 2020 are the focus of this report, as a snapshot in time of the capacity for resilience.

2.1.3 Resilience Frameworks in the Scientific Literature

The challenge of measuring resilience is one addressed in numerous ways across scientific disciplines, geographies, and focal topics. In 2017, the National Institute of Standards and Technology compiled an inventory of both conceptual and applied resilience frameworks, finding 58 different frameworks, each with a wide range of complexity and comprehensiveness (Loerzel and Dillard, 2021). An additional 17 resilience frameworks published between 2018 and 2022 were identified for this study. Both searches focused on frameworks specifically targeting resilience, excluding commonly used frameworks on related concepts such as the Social Vulnerability Index used by the Centers for Disease Control and Prevention and EJScreen created by the Environmental Protection Agency. The resulting 75 frameworks were further reviewed for best fit within this study's application (see Appendix A for the full list). Nine frameworks were identified (Table 1) that met the following criteria:

1) relied on secondary data only
2) successfully implemented in at least one case study, rather than just conceptualized
3) used data sources with available time series
4) had a topical focus related to NOAA's jurisdiction of coastal communities and/or natural hazards

The frameworks that fit the criteria varied in complexity both in how many total measures were included and how they were organized into broader thematic domains. From these nine frameworks, further investigation was limited to five frameworks that ranged in domain complexity and were not duplicative of one another (for example, Tract-level Baseline Resilience Indicators for Communities [TBRIC] is an adaptation of Baseline Resilience Indicators for Communities [BRIC] for smaller spatial resolution). After data availability for all coastal counties was checked, this set of five was further narrowed to three after it was determined that full implementation of two frameworks, PEOPLES and MRV (defined in Table 1), would require new data collections to fulfill their metrics and successfully adapt to U.S. conditions.

Table 1. List of existing indices of resilience that fit the criteria for inclusion in this study, ordered by complexity, i.e., number of measures. Those highlighted in orange were further considered for an NCCOS context as they spanned the complexity scale, were not duplicative of one another, and were implemented successfully at least once.

Framework Name	Number of Domains	Number of Measures	Citations
Cumulative Resilience Screening Index (CRSI)	5	108	Summers et al., 2020, 2022
Population and demographics, Environmental and ecosystem, Organized governmental services, Physical infrastructures, Lifestyle and community competence, Economic development, and Social-cultural capital (PEOPLES)	7	91	Cimellaro et al., 2016; Cardoni et al., 2021; Renschler et al., 2010; De Iuliis et al., 2022
Tract-level Baseline Resilience Indicators for Communities (TBRIC)	6	67	Derakhshan et al., 2022b
Baseline Resilience Indicators for Communities (BRIC)	6	49	Cutter et al., 2014, 2016; Cutter and Derakhshan, 2020
Measuring Resilience and Vulnerability (MRV)	4	37	Miller et al., 2016
Resilience to Emergencies and Disasters Index (REDI)	4	22	Kontokosta and Malik, 2018
Community Intrinsic Resilience Index (CIRI)	4	13	Gerges et al., 2022
Community Resilience Estimates (CRE)	1	10	U.S. Census Bureau, 2023
Resilience Inference Measurement (RIM)	3	3	Lam et al., 2016

The varying complexity of frameworks published in the scientific literature implies an empirical question of what level of complexity is necessary to meaningfully quantify resilience. Additionally, does the level of needed complexity vary by context? At one end of the spectrum, the Community Resilience Estimates (CRE) provided by the U.S. Census Bureau consist of a single domain of 10 individual and household measures from the American Community Survey (ACS). These include metrics of poverty, overcrowding, language barriers, employment, disability, health insurance coverage, age, vehicle access, and internet access. The CRE contains metrics that entirely overlap with common social vulnerability approaches, such as those in the Social Vulnerability Index (SoVI) developed by Cutter et al. (2003) and Fleming et al. (2022). While social systems are a key component of measuring resilience, the CRE fails to account for additional institutional, infrastructural, and environmental factors that can support preparedness, resistance, recovery, and adaptation within a community. As a result, the present study does not delve deeper into the CRE methods. The fact that literature and existing frameworks of resilience rely on differing underlying definitions is an important conclusion of considering CRE.

Cutter et al. (2008) developed the Disaster Resilience of Place (DROP) model, which depicts a quantifiable relationship between vulnerability and resilience that acknowledges various forms of resilience. BRIC, an index-based metric composed of 49 measures across six domains, is a demonstration of the DROP model and provides a quantification of a community's inherent resilience (Cutter et al., 2014). BRIC is also an excellent example of adaptability to different types of geographic areas, as an additional 16 measures of resilience were added when downscaling the approach from the county to the census tract level for the U.S. Gulf Coast (Derakhshan et al., 2022b). Another framework, PEOPLES, also explicitly includes methods for scaling to particular geographic contexts and offers the option of not using all seven domains in a given analysis. Researchers employing PEOPLES in geographies other than its original implementation utilized this option, citing data availability as a major limiting factor for full implementation of the 91-measure index (Cardoni et al., 2021; De Iuliis et al., 2022). Adaptations of both BRIC and PEOPLES showed that data availability is especially challenging for abstract, generally qualitative concepts such as place attachment that are often not monitored over time or across a wide geography and instead require, or at least benefit from, direct primary data collection.

Looking across the existing frameworks that fit the criteria for inclusion in this study, two frameworks were chosen for replication, CRSI and BRIC. They were chosen because they have been widely adopted by other researchers and because they offered two different levels of complexity. CRSI, which is highly complex, includes the most metrics of any of the frameworks and is by far the most complex in its approach to the different contributing factors of resilience (even including risk). BRIC, a framework of medium complexity, is more focused on the human dimensions of resilience and relies on far fewer measures. Therefore, BRIC might work better in contexts with potentially overlapping analyses such as models of risk. The two frameworks also represent different disciplinary approaches to resilience: BRIC emerges from hazards geography where factors are included that influence the ability to prepare for, respond to, recover from, and adapt to risks, while CRSI emerges from risk assessment and explicitly measures risk and then adds how that risk may be exacerbated by other factors. These approaches create two distinctive tools that should be deployed differently.

2.2 Data Preparation

Three key types of data were gathered and processed for comparison in this study: resilience frameworks, disaster declarations, and restoration investments. The resilience frameworks encompass numerous contributing datasets, detailed in Table 2. Compiling and correlating these datasets answered the first and second research goals detailed in the Introduction. The disaster declarations and restoration investments addressed the third research goal.

2.2.1 Resilience Frameworks

This study aimed to evaluate frameworks for quantifying resilience for use within a NOAA (e.g., coastal community) context and therefore replicated the available documented methodologies as closely as possible.

2.2.1.1 CRSI

CRSI consists of 120 individual measures organized into five domains: Built Environment, Natural Environment, Society, Governance, and Risk (Table 2). It was originally built as a snapshot in time based on 2015 data by the U.S. Environmental Protection Agency for every county in the U.S. CRSI construction pulls together previously existing indicators from each of the domains into one comprehensive measure; therefore, these domain scores are designed to be used individually as well.

Table 2. The five domains and associated indicators of the Cumulative Resilience Screening Index (CRSI). See Appendix B for specific data sources and implementation of these measures.

Domains	Indicators		
Built Environment (BE)	Air transportation facilities Bridge rating Bridges Cell towers Drinking water supply Energy production	Freight rails Highway access Internet access Paging access Radio access Roads – arterial	TV access Vacant buildings Vacant business structures Vacant residential structures Wastewater treatment
Governance (GOV)	Community Rating System Recovery funding	Flood insurance Homeowners insurance Income inequality	Protected lands
Natural Environment (NE)	Agriculture Air quality Biodiversity Coastal condition Coastal water Food access	Forest condition Forest cover Fresh water cover Grassland cover Ice cover Lake condition	Protected areas River condition Soil productivity Tundra cover Wetland condition Wetland cover
Risk	Coastal flooding Contaminants Drought risk Earthquake risk Fire exposure Habitat loss	Hail exposure High temperature exposure Hurricanes Inland flooding exposure Landslide exposure Low temperature exposure	Nuclear exposure Property damage Tornado exposure Tornadoes Wind exposure
Society (SOC)	Age Ambulance Asthma rate Blood banks Cancer rate Childcare availability Civic organizations Concrete Construction Diabetes rate Economic diversity Education Elderly living alone Employment Ethnic isolation Health access Health insurance Healthcare access Heart disease	Highway construction Home plumbing Hospital beds Housing age Housing density Income Insurance claims Language competency Law enforcement Legal and security Masonry services Migration Mobile homes Obesity Physician access Poverty rate	Power construction Psychiatric care Public safety services Rehabilitative services access Religious organizations Roofing construction services Schools Social services Special needs population Special needs transportation Steel construction Stroke Water and sewer construction

In this study, CRSI was recreated by updating the original data sources with 2020 versions for only the coastal shoreline counties. For datasets such as those from the Homeland Infrastructure Foundation–Level Data (HIFLD) that vary in availability, the most recent data were used. Other datasets were not available from the originally listed sources (e.g., Land Protection Priority Index, biodiversity, heart disease incidence, stroke incidence, cancer incidence, and insurance agencies), so new sources were employed instead (Appendix B), where the measure could be replicated from a different data provider.

Other measures required computation from raw data, but the available literature lacked the level of detail necessary to replicate the original methodology. As a result, the best available indicator was selected for measures on natural land loss, medically underserved areas, and earthquake risk, in consultation with researchers providing those data and mimicking what detail was available in the literature. Individual measures were min-max normalized and summed by domain, then normalized again on a scale of 0–1. Three of the domains (social, built environment, and natural environment) were adjusted to represent difference from the median for that domain in order to meet the needs of the whole index calculation. The whole index was calculated from domain scores as described in the original CRSI documentation (Summers et al., 2020), according to the following formula, where Gov is the governance domain score, SOC is the adjusted social domain score, BE is the adjusted built environment domain score, NE is the adjusted natural environment score, and Risk is the risk domain score:

$$CRSI_i = \frac{Gov_i + SOC(a)_i Gov_i + BE(a)_i + Gov_i + NE(a)_i Gov_i}{\text{Risk}}$$

2.2.1.2 BRIC

BRIC consists of 49 indicators across the following six domains: Social Resilience, Economic Resilience, Community Capital, Institutional Resilience, Housing/Infrastructural Resilience, and Environmental Resilience (Table 3). Each domain metric is used to calculate an overall additive index of total resilience.

Table 3. The six domains and associated measures of the Baseline Resilience Indicators for Communities (BRIC). See Appendix B for specific data sources and implementation of these measures.

Domains	Indicators	
Social Resilience	Age Communication capacity Education English competency Food supply	Health insurance Physician access Psychiatric care Special needs population Transportation
Economic Resilience	Business size ratio Business size employees Employment Federal employment Gender income equality	Homeownership Income equality Non-dependence on tourism sectors Retail geographic distribution
Community Capital	Citizen preparedness Civic organizations Disaster volunteers	Place attachment Political engagement Religious organizations
Institutional Resilience	Crop insurance Disaster aid experience Disaster training Flood insurance Jurisdictional coordination	Mitigation spending Nuclear accident planning Performance regimes-nearest metro area Performance regimes-state capital Population stability
Housing/Infrastructural Resilience	Evacuation Hospital beds Housing construction quality Industrial re-supply potential	Internet access Schools Sturdier housing Temporary housing Temporary shelters
Environmental Resilience	Energy use Local food supply Pervious surfaces	Water use Wetland cover

BRIC index values and maps are publicly accessible for 2010, 2015, and 2020 for U.S. counties (excluding Hawaii and Alaska in 2010) (University of South Carolina Hazards and Vulnerability and Research Resilience Institute, 2023). These publicly accessible data, however, include only the final index values that were calculated relative to all U.S. counties. As this study is focused on coastal communities, BRIC calculations were replicated based on methods outlined in the literature (Cutter et al., 2014) to understand data source availability and metric calculations within the context of U.S. coastal counties. This exercise provided insight for potential future applications in scaled-down place-based analyses, as will be discussed later.

Data sources originally used by Cutter et al. (2014) were available for the year 2020 for all measures except mental health support, food provisioning capacity, jurisdictional coordination, volunteerism, citizen disaster preparedness and response skills, local disaster training, and efficient water use (Appendix B). These data sources were either no longer accessible, not publicly accessible, or not available for the year 2020. Alternative data sources, identified via substitute variables tested by Derakhshan et al. (2022b), were used when the original data source used by Cutter et al. (2014) was no longer accessible or publicly available. In cases where 2020 data were not yet available, the best available and most recent data were used.

Individual measures were normalized to a scale of 0–1 using min-max rescaling. Values were then computed for each of the six domains by calculating the mean of measures falling within each domain. Missing values were excluded from these calculations rather than being imputed. An additive index of total resilience was calculated for each coastal county by summing the six domain metrics, with possible index values ranging from 0 to 6.

This study aimed to strictly follow the original BRIC methodology, but a review of 32 implementations of BRIC found that local adaptations were almost always warranted as it performed differently in varying contexts (Camacho et al., 2023). While the definition of measures was not changed for this study, the necessary use of substitute data sources deviated it from the original methodology. Multivariate analyses to test for variance, multilinearity, or internal consistency were not performed, but these should be explored in future scaled-down studies to inform weighting and computation of the overall index.

The available literature did not detail how to handle missing values, which existed across several measures and for some counties. Depending on the measure and data source, some missing values were assigned a value of zero when relevant; this was a common approach for the Institutional and Housing/Infrastructural domain measures such as public schools or evacuation routes. Alternatively, unanticipated missing values were assigned a null value and excluded from the final domain and index calculations. The way that missing data were handled (e.g., assigning a value of null or zero) for each indicator is described in Appendix B.

2.2.2.3 Recreating BRIC Versus Original Values

The Hazards and Vulnerability Research Institute (HVRI) continues to update the BRIC methodology between data releases to reflect changes in data availability and performance of those indicators in recent implementations of BRIC. The HVRI team compared their scores for coastal counties and the NCCOS-replicated version and found differences in the top 10 resilient counties, primarily with Wisconsin scoring higher in the HVRI method.

Some key differences between the NCCOS-replicated coastal BRIC scores and the 2020 release of nationwide BRIC data include 1) educational attainment measuring percentage of the population with associate's degree or above, 2) age measuring percentage of the population between 15 and 65, and 3) federal employment including both military and civilian federal employment. The HVRI team reported few cases of missing data but have also updated how they handle nulls from imputing the national average to considering true zeros and remaining nulls (especially in Alaska). Their reliability test of Chronbach's alpha on the 2020 HVRI BRIC data for the 357 coastal counties without nulls yields $\alpha = 0.524$. They could not complete a Chronbach's alpha on the NCCOS BRIC scores because the community and environmental domains had too many nulls. Both sets of BRIC component indicators contain several with negative covariances with the overall index score, which both causes a lower-than-expected alpha score and points at indicators that may benefit from inclusion in a different domain or updated construction.

2.2.2 Disaster Declarations

Data for presidentially declared disasters (PDDs) that occurred in the U.S. between the years 2000 and 2020 were downloaded from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database (Center for Emergency Management and Homeland Security, 2023). All declaration types were included. The raw data were provided in aggregate form summarized by county and year and included information on the number of PDD events and the total dollar amount of property damage (inflation-adjusted to 2020 dollars) from those collective events. Dollar amounts were then summed for each coastal county and divided by county populations to calculate dollar amounts in damage per capita.

2.2.3 Restoration Funding

Restoration investment data were obtained from the Restoration and Conservation Database (RCDB) of the NOAA Restoration Center (NOAA NMFS, 2023). For this project, consideration was given to NOAA contributions that were funded through the American Recovery and Reinvestment Act (ARRA) of 2009. ARRA is a unique chance to evaluate a national-scale investment in infrastructure rather than the more typical funding allocated to recover from a disaster. As such, and given NOAA's jurisdictional authority, these projects touched more than what is included in the infrastructure or built environment domains, particularly in links to the environmental resilience and natural environment domains. Lessons from ARRA might be helpful in structuring future similar investments and in distributing allocated money from laws such as the Infrastructure Investment and Jobs Act of 2021. In particular, over 90% of the total amount contributed by NOAA on these restoration projects was funded through ARRA 2009. The data were aggregated by county by summing the number of projects and dollar amount invested for each county. Total investment amounts were then divided by county populations to calculate per capita investment for each county.

2.3 Spatial and Statistical Analyses

Resilience metrics, disaster declarations, and restoration investments were joined tabularly and georeferenced to the 397 coastal shoreline counties identified for the year 2020 using Microsoft Excel and ArcGIS Pro 3.0. Each coastal county was assigned to one of seven regions: Alaska, Great Lakes, Gulf of Mexico, Northeast, Hawaii, Southeast, and West Coast (Figure 1). The resilience metrics used within the spatial and statistical analyses included the 2020 CRSI and BRIC values, which were adapted from the literature (Cutter et al., 2014; Summers et al., 2020) and calculated relative to shoreline counties.

2.3.1 Spatial Analysis

Spatial patterns in the data were assessed by classifying the data into tertiles, determining the frequency of low and/or high values across regions, and exploring overlapping trends across pairs of variables. Overlapping spatial trends across varying combinations of two variables were visualized using bivariate choropleth maps in ArcGIS Pro 3.0. Figure 2 displays the legend for a bivariate choropleth of CRSI and BRIC indices. Bivariate choropleths allow for a visualization of the agreement or disagreement across the indices. If the primary goal or application of this work were to site the location of future place-based studies, then counties in which both indices agree on low resilience (gray) would likely be of interest. Similar conclusions could be drawn looking at overlaps between the resilience indices and restoration funding or disaster impacts. For example, if one were to look at the intersection between BRIC and restoration funding, future restoration sites could be prioritized in areas where there is low resilience and low restoration investment.

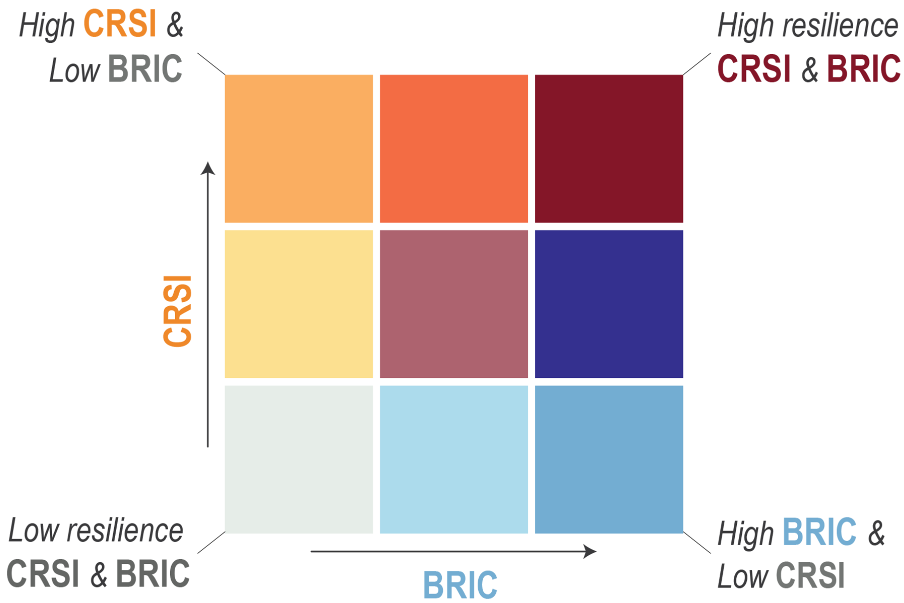


Figure 2. Legend for a bivariate choropleth of CRSI and BRIC indices. Lower resilience values in the first tertile of data fall in the lower left (gray) corner of the legend, while the highest resilience values fall on the bottom right (blue; BRIC) and top left (orange; CRSI) and right (red; both indices).

2.3.2 Statistical Analysis

All four final datasets were first checked for normality and a comparative linear relationship to determine the best approach to measure relatedness. Because BRIC and CRSI are neither normal nor linear, Spearman's correlations were used to test the monotonic relationship between BRIC and CRSI as well as the relationship between each index with PDDs and restoration investments. Because Spearman's is a rank correlation test, the entire dataset was used for these correlation tests, including the high CRSI values observed in Alaska. After outliers at the 95% confidence interval were removed, a principal component analysis and multiple linear regression on domain scores were used to determine the relative contribution to the variance of each of the domain scores and overall resilience indices, respectively.

In terms of restoration investments, counties were categorized into two groups: those that did not receive restoration investments and those that received funding for at least one project. Counties with any amount of funding were compared to resilience scores to investigate possible relationships between funding and indicated resilience.

Counties were also categorized in terms of PDDs: those that experienced fewer than 10 PDDs and those that experienced 10 or more PDDs. Then, BRIC and CRSI domains and indices were compared using Wilcoxon rank sum tests of medians to determine if there was any relationship between disaster declarations and resilience scores.

Chapter 3: Summary of Results

3.1 Resilience

3.1.1 Resilience in 2020

Resilience measures varied by framework and ultimately by what concepts were included in their definition of resilience. Most notably, CRSI included a Risk domain while BRIC did not. For the first comparison of full-index scores, this analysis investigated how different these indexes performed. Afterward, BRIC was compared to CRSI without its risk domain for better alignment between domains.

Tables 4 and 5 display the CRSI and BRIC index scores for the 10 most resilient and 10 least resilient coastal counties (see Appendix C for more details). According to the CRSI scores, counties with higher resilience appeared to have low levels of risk and were all in Alaska and Michigan. Counties with higher resilience according to BRIC appeared to have higher scores within the Social and Environmental domains. None of the top and bottom 10 counties aligned across the indices; in fact, the two indices found opposing ratings for the Aleutians East Borough in Alaska (see Figure 3 for a map of index agreement).

Table 4. CRSI scores for the 10 most resilient and 10 least resilient counties in 2020. Cells are color-coded according to ranges across all counties, with red indicating low scores and blue indicating high scores. Scores are relative to other coastal counties due to normalization, so a value of zero risk does not mean no risk was present, just that it was lowest on the scale of risk factors calculated.

	County	Risk	Governance	Society	Built Environment	Natural Environment	CRSI Total Resilience
1	Dillingham Census Area, AK	0.00	0.26	0.42	0.18	0.06	9740.28
2	Benzie County, MI	0.00	0.58	0.57	0.17	0.30	838.38
3	Bethel Census Area, AK	0.00	0.59	0.25	0.33	0.29	330.06
4	Alcona County, MI	0.00	0.52	0.40	0.20	0.31	185.08
5	Alpena County, MI	0.00	0.60	0.44	0.15	0.32	180.59
6	Nome Census Area, AK	0.00	0.53	0.34	0.26	0.18	169.37
7	Copper River Census Area, AK	0.00	0.23	0.42	0.24	0.23	148.43
8	Hoonah-Angoon Census Area, AK	0.00	0.23	0.59	0.16	0.73	147.28
9	Ketchikan Gateway Borough, AK	0.00	0.24	0.54	0.11	0.71	137.41
10	Aleutians East Borough, AK	0.00	0.23	0.63	0.11	0.36	133.99
388	Kewaunee County, WI	0.37	0.00	0.79	0.16	0.40	0.00
389	Baltimore City, MD	0.49	0.22	0.18	0.17	0.16	−0.02
390	Kleberg County, TX	0.19	0.46	0.23	0.14	0.17	−0.11
391	Washington County, ME	0.24	0.54	0.14	0.16	0.21	−0.12
392	St. Lucie County, FL	0.19	0.28	0.12	0.14	0.18	−0.42
393	Iberia Parish, LA	0.23	0.62	0.14	0.12	0.23	−0.48
394	Hernando County, FL	0.21	0.47	0.12	0.20	0.09	−0.61
395	Tillamook County, OR	0.20	0.55	0.27	0.07	0.12	−1.29
396	Coos County, OR	0.25	0.64	0.26	0.13	0.00	−1.37
397	Lincoln County, OR	0.23	0.56	0.14	0.09	0.11	−1.82

Table 5. BRIC scores for the 10 most resilient and 10 least resilient counties in 2020. Cells are color-coded according to ranges across all counties, with red indicating low scores and blue indicating high scores. Scores are relative to other coastal counties due to normalization.

	County	Social	Economic	Housing/ Infrastructural	Community Capital	Institutional	Environ-mental	BRIC Total Resilience
1	St. James Parish, LA	0.53	0.56	0.67	0.40	0.26	0.68	3.10
2	Cameron Parish, LA	0.54	0.44	0.61	0.49	0.29	0.65	3.03
3	Brown County, WI	0.58	0.56	0.55	0.41	0.33	0.58	3.01
4	Cumberland County, ME	0.60	0.57	0.52	0.39	0.33	0.60	3.00
5	Plymouth County, MA	0.58	0.54	0.53	0.42	0.31	0.60	2.98
6	St. Louis County, MN	0.56	0.53	0.46	0.37	0.35	0.69	2.97
7	Dare County, NC	0.51	0.56	0.38	0.48	0.36	0.68	2.97
8	Ozaukee County, WI	0.61	0.52	0.52	0.39	0.31	0.61	2.96
9	Lake County, OH	0.54	0.57	0.57	0.42	0.31	0.56	2.95
10	Sheboygan County, WI	0.59	0.56	0.48	0.39	0.32	0.62	2.94
388	Aleutians East Borough, AK	0.47	0.46	0.21	0.20	0.17	0.64	2.15
389	Kings County, NY	0.53	0.48	0.25	0.28	0.33	0.26	2.12
390	Skagway Municipality, AK	0.50	0.45	0.05	0.24	0.25	0.63	2.11
391	Aleutians West Census Area, AK	0.56	0.48	0.02	0.23	0.21	0.61	2.11
392	Kenedy County, TX	0.33	0.28	0.45	0.27	0.36	0.38	2.07
393	Copper River Census Area, AK	0.54	0.57	0.21	0.00	0.25	0.50	2.06
394	Bronx County, NY	0.48	0.40	0.20	0.30	0.36	0.29	2.04
395	Chugach Census Area, AK	0.55	0.55	0.14	0.00	0.28	0.50	2.02
396	Hoonah-Angoon Census Area, AK	0.36	0.40	0.16	0.15	0.21	0.64	1.93
397	North Slope Borough, AK	0.55	0.45	0.19	0.18	0.20	0.33	1.91

Figure 3 displays where CRSI and BRIC total resilience indices agreed and disagreed, according to a tertile classification, and the lower right quadrant of Figure 4 shows numerical correlations between the two indices. There are a number of counties in the Great Lakes region in which both indices suggested communities may have higher resilience. Further, there are counties scattered across the country in which both indices implied communities have lower resilience (gray); these areas can be seen highlighted in gray throughout the West Coast, Gulf of Mexico, and parts of the Southeast. Differing index scores were not surprising and could be partially attributed to differing definitions of what contributed to resilience, which in turn led to different contributing data domains. Additionally, the operationalization of these definitions may perform differently in rural and populous regions (Cutter et al., 2016a).

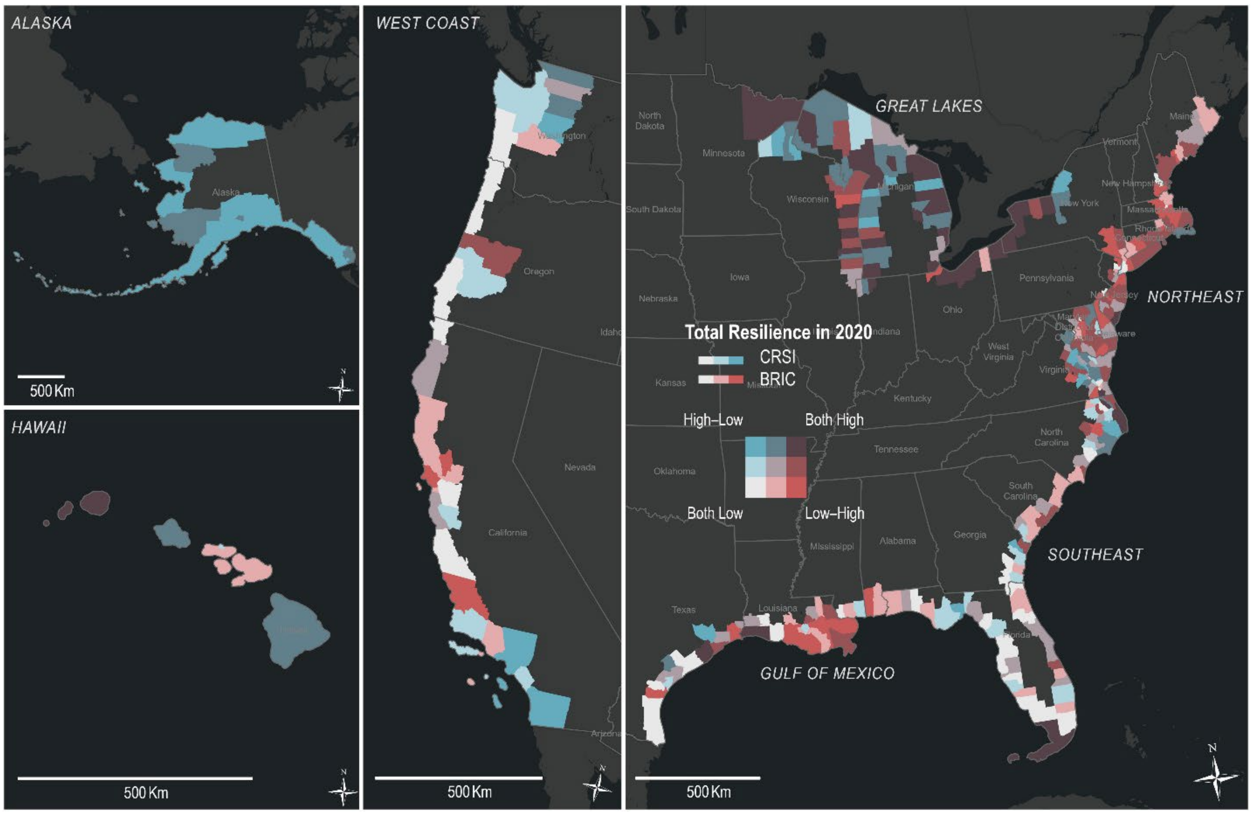


Figure 3. Bivariate choropleth map showing coastal counties where CRSI and BRIC total resilience scores agreed and disagreed.

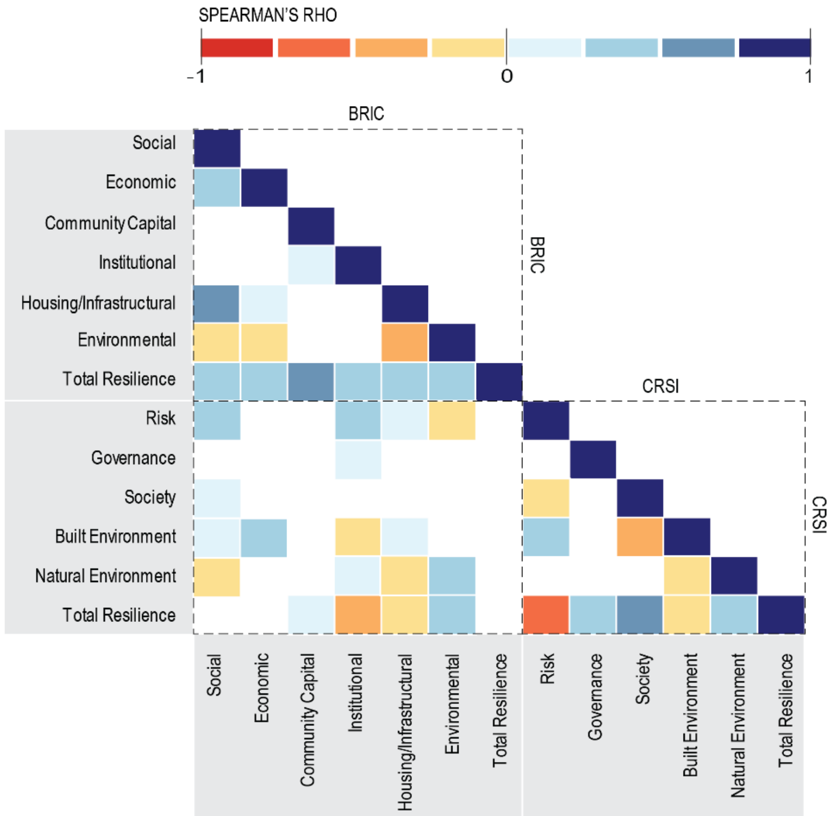


Figure 4. Spearman's rank correlation matrix between the different domains of BRIC and CRSI. Color indicates the intensity of rho values and whether the relationship is positive (blue) or negative (red). Only significant correlations ($p \leq 0.01$) are shown.

The 2020 CRSI and BRIC total resilience indices were not at all linearly correlated ($r^2 = 0.02$, $p = 0.004$) and were also not rank correlated (Spearman's rho = 0.017, $p = 0.74$) (Figure 4). Note that this was expected given the differing definitions of resilience. The level of correlation between CRSI and BRIC varied across the nation—the two indices agreed more in some regions than in others but remained not significantly correlated when broken down by region (Table 6). In some regions, the two indices trended in opposite directions. For example, in the Great Lakes, CRSI and BRIC were negatively correlated. This was likely due to low scores in the Risk domain that were incorporated into CRSI but not in BRIC. Regions were not uniform in this pattern. In the West Coast, CRSI scored higher in most places, but BRIC scored higher in the San Francisco Bay region; this was still an inverse relationship between the two indices, but patterns emerged at the scale of a cluster of counties and therefore showed no regionwide trends.

Table 6. Spearman's rank correlation results of 2020 total resilience measures for CRSI and BRIC by region.

Region	Spearman's Rho	P Value
Gulf of Mexico	0.010	0.935
Alaska	0.111	0.589
West Coast	0.111	0.484
Northeast	0.045	0.629
Southeast	0.059	0.674
Hawaii	0.800	0.104
Great Lakes	−0.256	0.020

3.1.2 Testing Different Definitions of Risk

Because including risk as a domain in CRSI and not in BRIC created a theoretical and definitional divide between the two indices, it was a fairer test to compare the two after removal of the risk domain from CRSI. Recalculating an amended CRSI without the risk domain was expected to better correlate and compare with BRIC. An amended CRSI was therefore calculated by adding the domain scores for each of the non-risk domains, and that result was compared with BRIC both spatially and statistically (Figure 5). This resulted in a similar patchwork of scores across the country as a whole; however, the CRSI score for many western states—especially Alaska—dropped from high to a lower category.

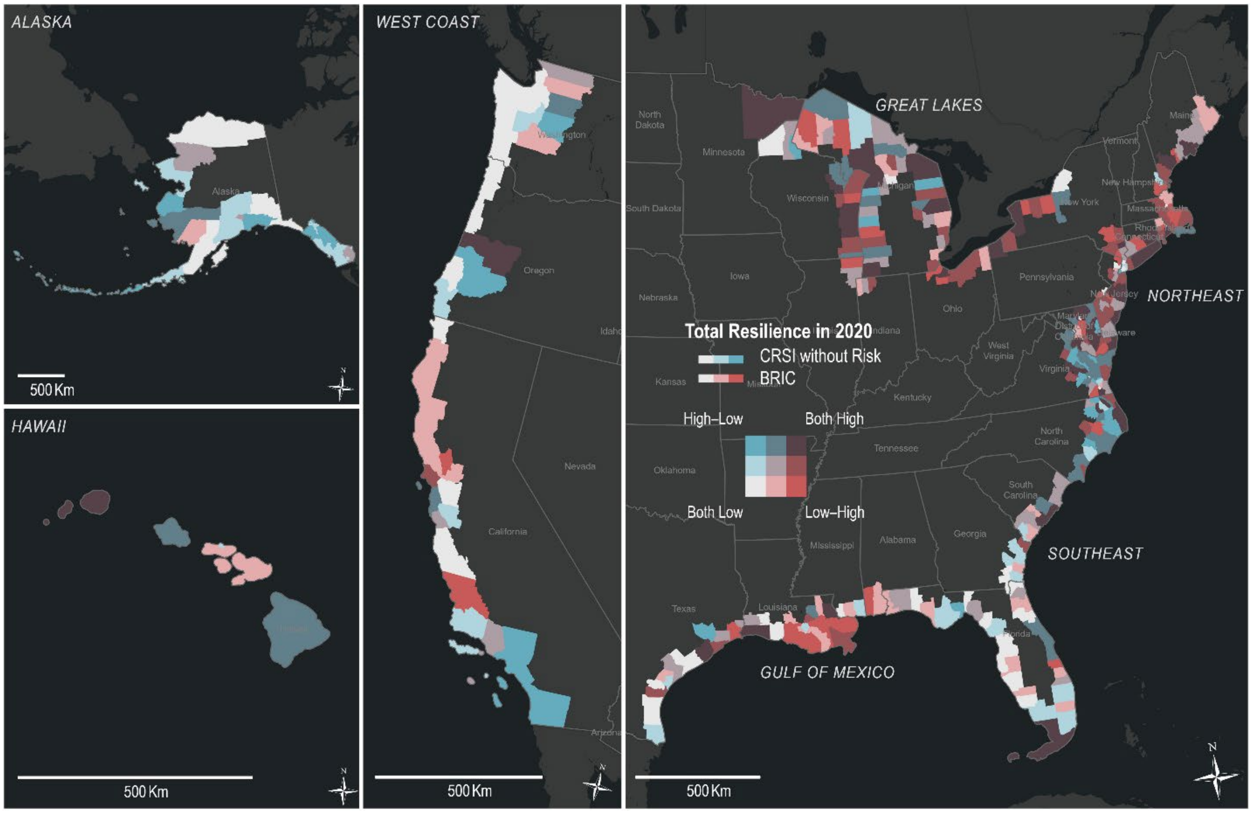


Figure 5. Bivariate choropleth map showing coastal counties where CRSI (without Risk) and BRIC total resilience scores agreed and disagreed.

The 2020 amended CRSI and BRIC total resilience indices were not at all linearly correlated ($r^2 = 0.02$, $p = 0.004$) but were slightly rank correlated (Spearman's rho = 0.16, $p = 0.00$) (Figure 6). Individual BRIC domains were no longer correlated, negatively or positively, with the total amended CRSI score. Regional correlations were now not significant across the nation, though the West Coast was now close to significance ($p = 0.097$). On the whole, amending CRSI to have a closer definition of resilience did not increase the correlation between the two indices as expected. There remain many other conceptual differences in how these indices were framed that apparently accounted for a large portion of the quantitative differences.

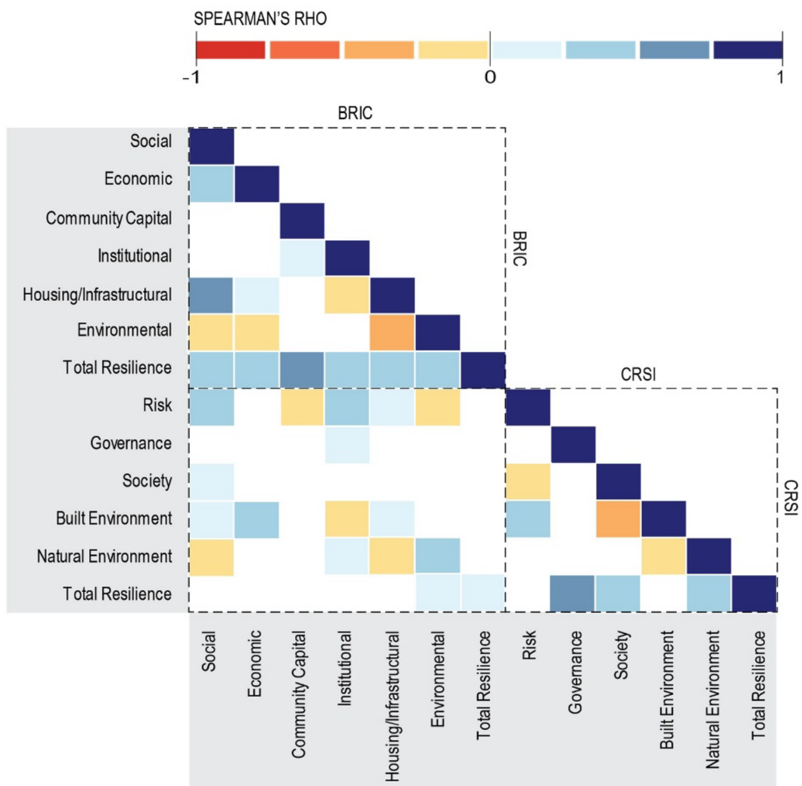


Figure 6. Spearman's rank correlation matrix between the different domains of BRIC and CRSI recalculated without the risk domain. Color indicates the intensity of rho values and whether the relationship is positive (blue) or negative (red). Only significant correlations ($p \leq 0.01$) are shown.

Table 7. Spearman's rank correlation results of 2020 total resilience measures for the amended CRSI (without risk) and BRIC by region.

Region	Spearman's Rho	P Value
Gulf of Mexico	0.011	0.927
Alaska	-0.161	0.432
West Coast	0.260	0.097
Northeast	-0.009	0.920
Southeast	0.114	0.413
Hawaii	0.500	0.391
Great Lakes	0.158	0.157

3.1.3 Resilience Domains: Not All Tell the Same Story

The biggest difference between BRIC and CRSI is that CRSI included additional thematic areas in the form of domains addressing risk and governance. Even within CRSI, each domain did not necessarily tell the same story; as expected, the domain driving the overall resilience score varied by geography. The CRSI total resilience value was strongly negatively correlated with Risk ($r = -0.65$, $p < 0.001$) but directly correlated with Society ($r = 0.56$, $p < 0.001$) (note that because the individual domains were used in the calculation of the CRSI total, the directionality of the correlation was expected but the intensity was not) (Figure 4). This makes sense given the way CRSI was calculated with risk as a denominator, reflecting that communities dealing with repeated, multiple risks (aka a higher risk score) will have a harder time activating attributes of their community that raise resilience. Most correlations were not significant between individual domains, and those that were significant were mild inverses except for Risk and Built Environment ($r = 0.28$, $p < 0.001$), which was a mild direct correlation.

The BRIC total resilience value was significantly and directly correlated across all the domains, with a stronger relationship with the Community Capital domain ($r = 0.64$, $p < 0.001$). Significant, yet weak negative relationships were seen between the Environmental domain and the Social ($r = -0.19$, $p < 0.001$), Economic ($r = -0.14$, $p = 0.005$), and Housing/Infrastructural ($r = -0.32$, $p < 0.001$) domains. Conversely, there was a strong positive correlation between the Social and Housing/Infrastructural ($r = 0.50$, $p < 0.001$) domains.

Examining domain scores can help determine why a county may have scored a certain way. A principal components analysis revealed that all CRSI domains contributed similarly to the variance in the data and therefore were necessary to help represent resilience as defined by the CRSI. The resulting five PCA-derived dimensions were all necessary to explain at least 90% of the variance in the domain scores. In addition, the five domains split across all five components, though not quite as equally as with BRIC. The first two dimensions depicted in Figure 7 together explained 51% of the variance. These components dominantly comprised Built Environment, Governance, and Risk, with smaller contributions from each of the other domains. This dominance of Built Environment and Governance was similar across all regions, though in different proportions (as shown in Figure 7).

For another test of variance, multiple linear regression was also used to get a general idea of how much variance in the CRSI index could be explained by individual domains. Results showed all five domains collectively explained 66% of the variance in total CRSI scores, comprising overlapping contributions of the Risk ($r^2 = 0.21$), Governance ($r^2 = 0.07$), Society ($r^2 = 0.19$), Built Environment ($r^2 = 0.002$), and Natural Environment ($r^2 = 0.11$) domains (note that because of autocorrelation, the contributions do not add up to the total variance and are presented to show relative contributions compared to each other). These tests suggested that Risk, Society, and Natural Environment were the most important domains in determining overall CRSI score, while Built Environment, Governance, and Risk were the biggest contributors to variance across the study geography.

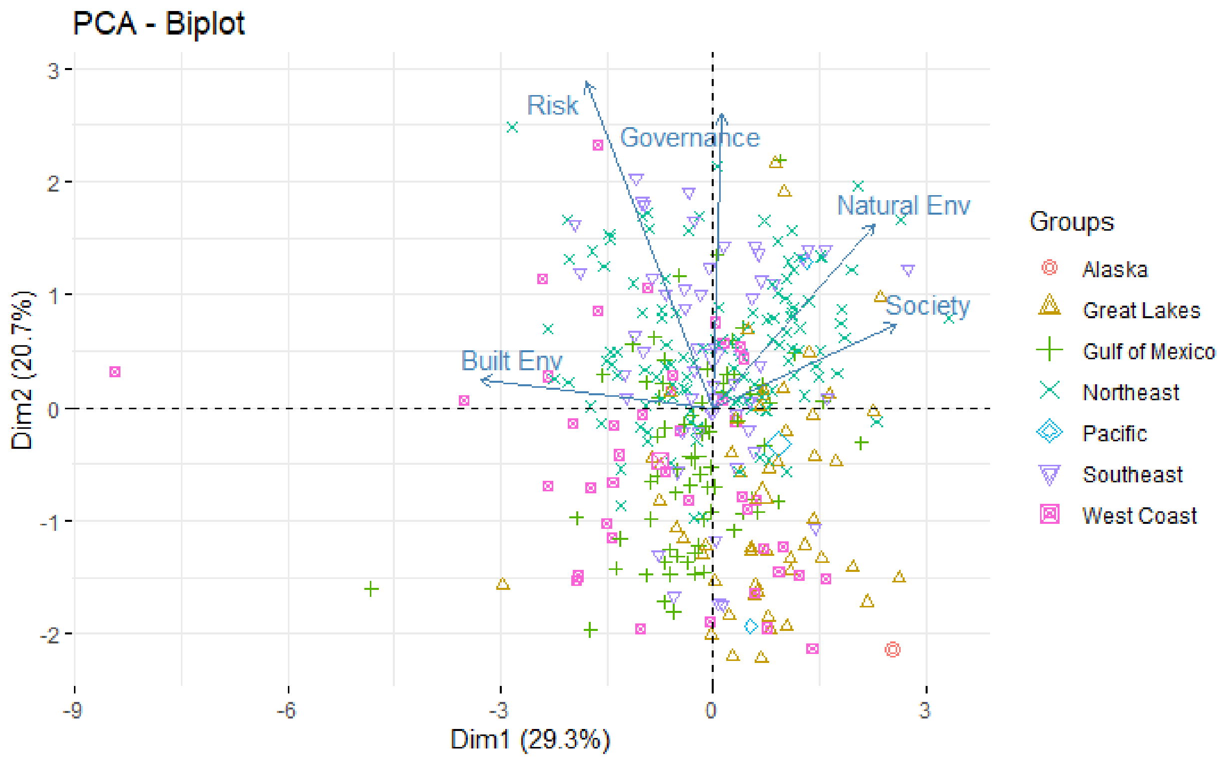


Figure 7. Biplot showing the first two components of a principal component analysis on CRSI domains, looking at the contributions of various domains to the variance in resilience, color coded by region. Outliers are omitted.

For BRIC, all domains contribute similarly to the variance in the data and therefore are necessary to help represent resilience according to BRIC. Of the six components created through a principal component analysis of the domains, five are necessary to explain more than 90% of the variance (93.4%). In addition, the six domains split across all the resulting components fairly evenly. The first two components together explain 58% of the variance, with no clear dominant contributions from a particular domain (Figure 8). The pattern is similar across regions. Multiple linear regression was used to get a general idea of how much variance in the BRIC index is explained by individual domains. All six domains collectively explain the total variance in resilience scores, comprising overlapping contributions of the Social (r^2 = 0.42), Economic (r^2 = 0.23), Housing/Infrastructural (r^2 = 0.11), Community Capital (r^2 = 0.19), Institutional (r^2 = 0.08), and Environmental (r^2 = 0.21) domains. This suggests that all the BRIC domains contribute to the overall score, with the Social domain playing the largest role in explaining the variance.

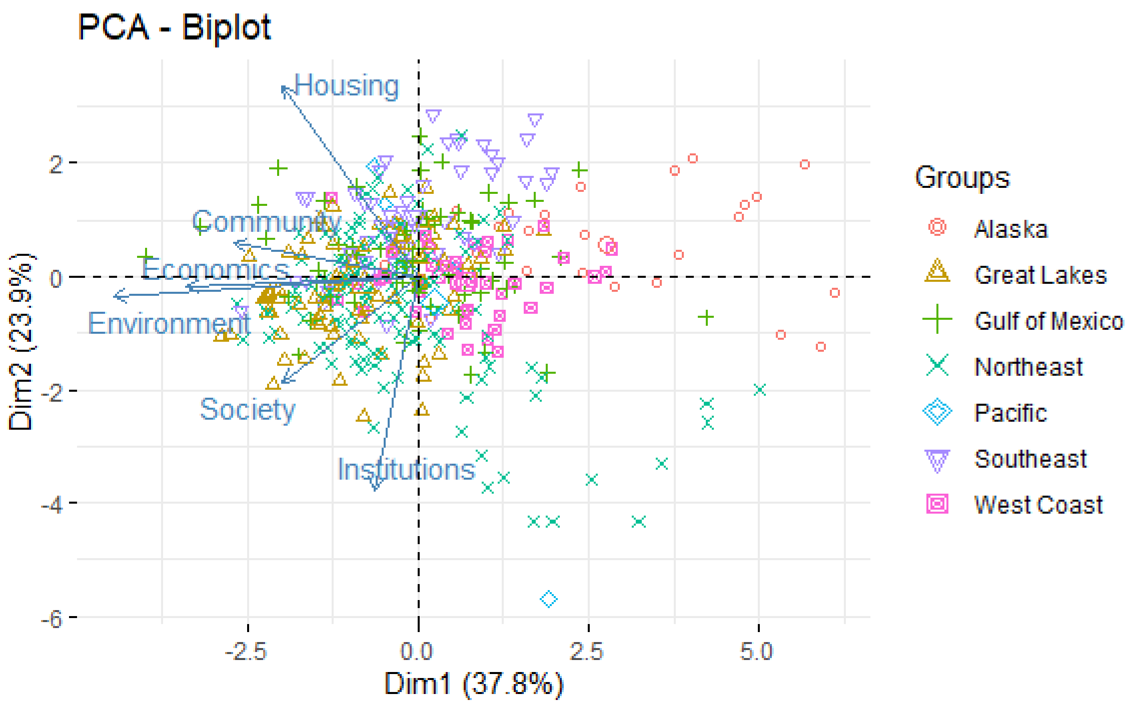


Figure 8. Biplot showing the first two components of a principal component analysis on BRIC domains, looking at the contributions of various domains to the variance in resilience, color coded by region.

3.2 Disasters

3.2.1 Summary of Presidentially Declared Disasters

Between the years 2000 and 2020, over 5,000 PDDs occurred across 363 (91%) of the 397 coastal counties in the study area. Almost half (45%, 179) of coastal counties experienced 10 or more PDDs (Figure 9). Counties in the Northeast region collectively experienced the most PDDs (31%, 1,563), followed by counties in the Gulf of Mexico region (30%, 1,526). The five states with the highest number of PDDs declared within their coastal counties were 1) Florida (708), 2) Louisiana (496), 3) California (389), 4) Texas (383), and 5) New York (360). San Diego County, California, experienced the most (165) PDDs during this period, followed by Harris County, Texas (104), and Plymouth County, Massachusetts (60).

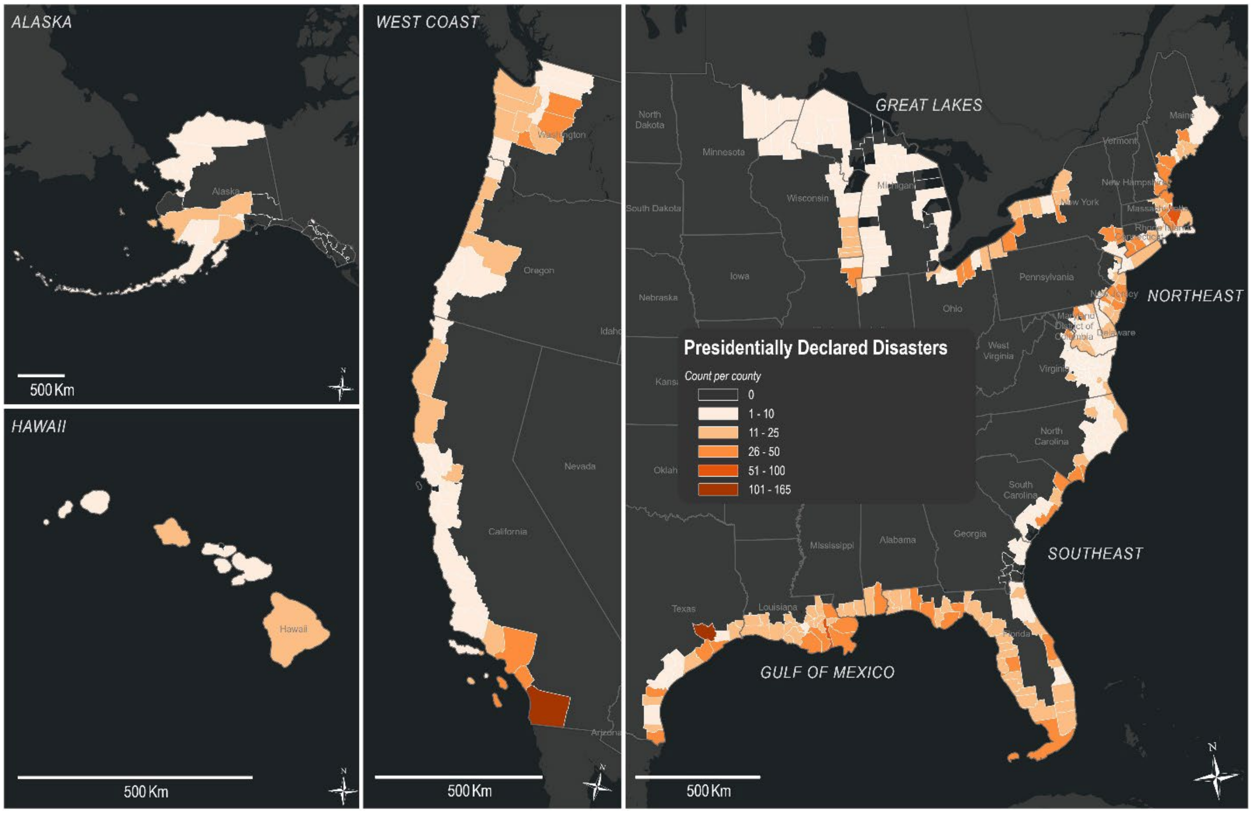


Figure 9. Map of the number of presidentially declared disasters (PDDs) per county from 2000 to 2020.

Counties in the Gulf of Mexico region held the highest mean per capita property damage due to PDDs ($73,772) followed by counties in the Southeast region ($5,150) (Figure 10). These are largely due to recent intense hurricane activity. For example, Cameron Parish, Louisiana, experienced the highest amount of property damage per capita ($1,721,214) after repeated hurricanes. In fact, Louisiana parishes make up five of the top 10 counties with the highest amount of property damage per capita. Moreover, all top 10 counties are located in the Gulf of Mexico region. PDDs in this region have also increased over time nationally, as have requests for federal assistance following natural hazards.

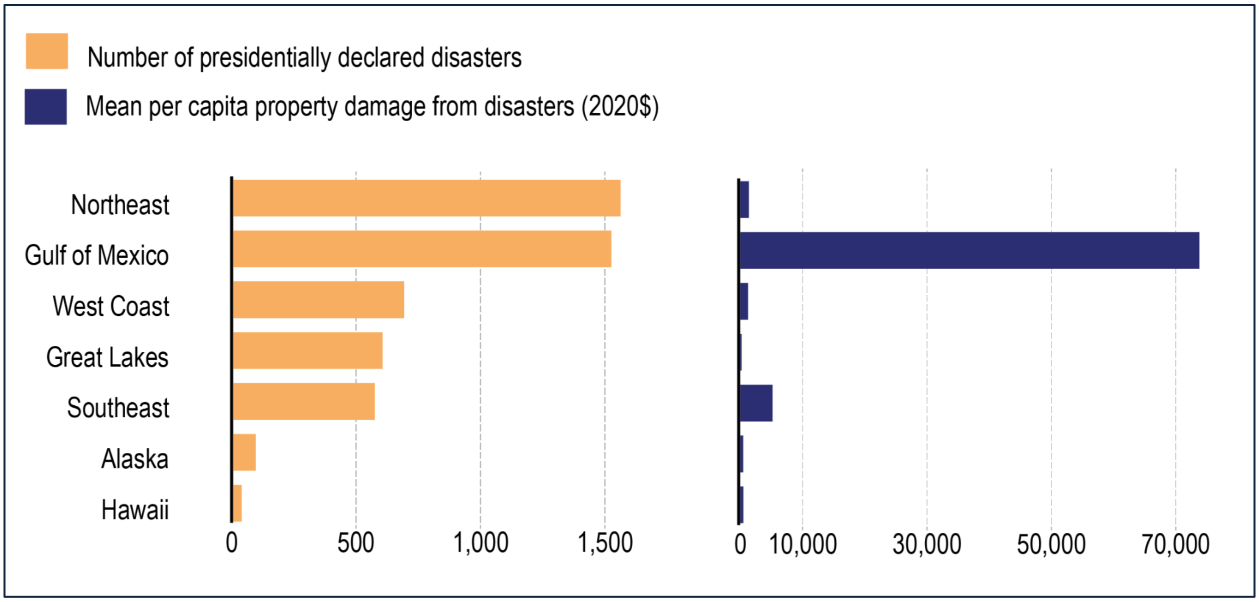


Figure 10. The number of presidentially declared disasters (orange) by region, and the mean property damage per capita in U.S.$ (2020) (blue) incurred from those disasters.

3.2.2 Presidentially Declared Disasters and Resilience

Figure 11 displays the spatial overlap between PDD per capita property damage and CRSI (Figure 11a) and BRIC (Figure 11b) total resilience. These maps highlight in mid-tone blue those counties in which damages per capita were high and total resilience scores were low; this combination of scores highlights places with an elevated need for support and future resilience building work. For CRSI, these counties are distributed throughout ocean-facing regions of the conterminous U.S., with key areas in the central Gulf of Mexico region and northern Oregon (Figure 11a). For BRIC, these counties are also distributed around the ocean-facing counties, with a similar cluster in the central Gulf of Mexico and one in New Jersey (Figure 11b). A handful of counties have experienced high damages but have high measures of resilience according to both indices: Monroe County, Florida; Dare County, North Carolina; and three counties in east Texas. Note that the disaster data reflect compounded effects over 20 years, capturing the stress associated with repeated disasters and the lingering effects a disaster can still have years later. The number of PDDs in any single year is too small to enable a geographic comparison.

(a)

(b)

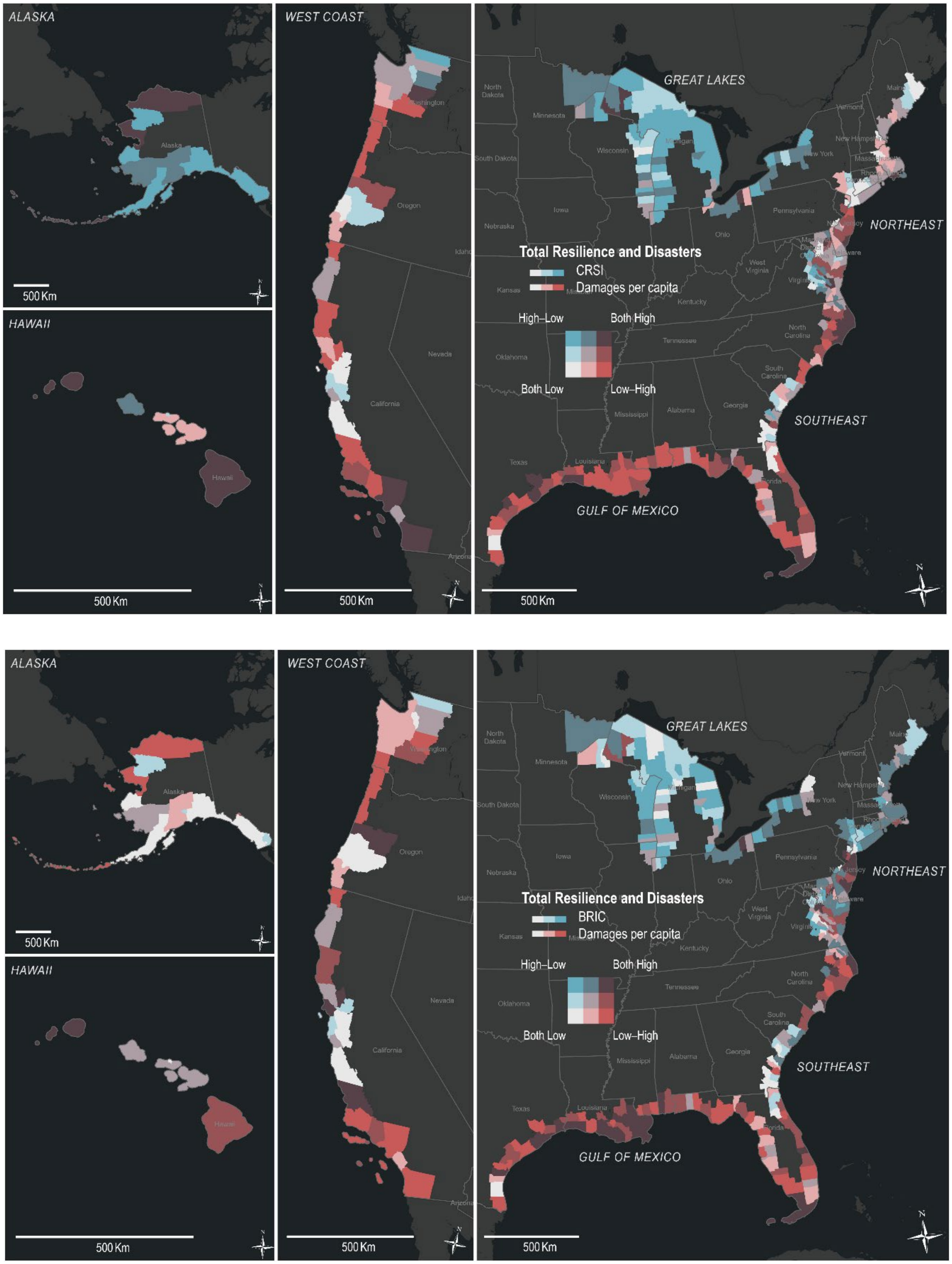


Figure 11. Bivariate choropleth maps of the intersection between (a) CRSI total resilience and damages per capita incurred from presidentially declared disasters and (b) BRIC total resilience and damages per capita incurred from presidentially declared disasters. Counties colored blue indicate areas where costs in damages were high and resilience scores were low.

No strong positive or negative correlations were found between the number of PDDs or per capita property damage with metrics of resilience. For instance, the highest, significant ($p < 0.01$) values of correlation coefficients found were moderate correlations between PDD events and CRSI Risk ($r = 0.31$), CRSI Society ($r = -0.37$), and CRSI Total Resilience ($r = -0.33$) (Figure 12). CRSI Risk is inherently about the types of hazards that produce disasters and includes an indicator of disaster relief spending, so a correlation is expected. Similarly, the highest significant values of correlation coefficients of per capita property damage were with BRIC Institutional ($r = 0.43$), CRSI Society ($r = -0.33$), and CRSI Total Resilience ($r = -0.25$). The BRIC Institutional domain included a measure of disaster aid experience that considered PDDs and loss-causing hazard events from this 10-year time range; given this conceptual overlap, seeing a positive correlation was expected.

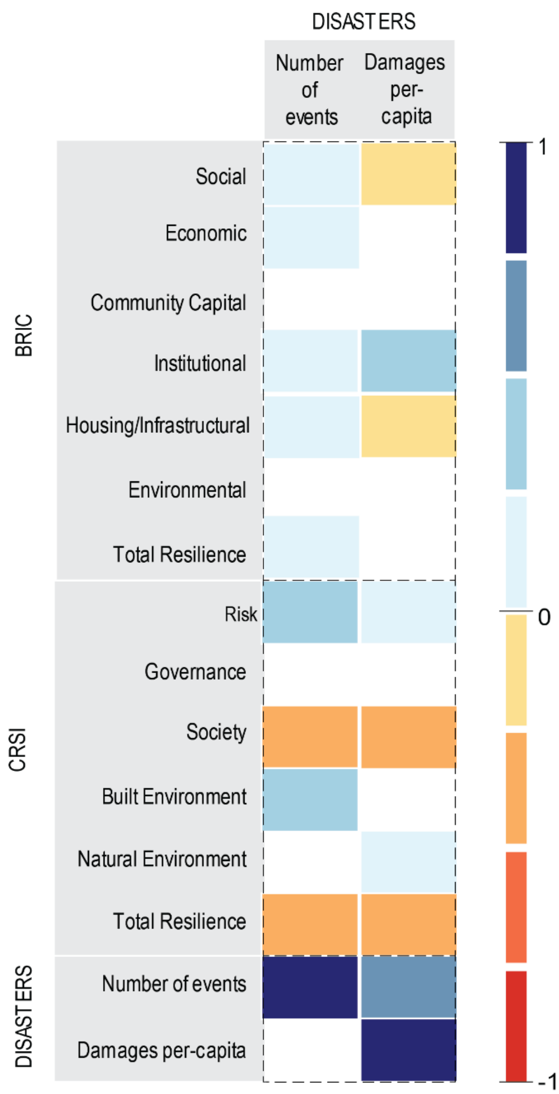


Figure 12. Spearman's rank correlation matrix between resilience measures and presidentially declared disasters. Color indicates the intensity of rho values and whether the relationship is direct (blue) or indirect (red). Only significant correlations ($p < 0.01$) are shown.

The Wilcoxon rank sum test of medians indicated that counties that experienced 10 or more PDDs had significantly higher values of BRIC's Economic Resilience, Institutional Resilience, and Total Resilience and CRSI's Risk and Built Environment domains compared to counties that experienced fewer than 10 PDDs. Alternatively, counties that experienced none or few PDDs had significantly higher values for CRSI's Society and Total Resilience domains.

Overall, the results suggest that counties that experienced higher numbers of PDDs and/or faced higher property damage due to PDDs were at higher risk but were more resilient in terms of the Economic, Institutional, and Built Environment domains.

3.3 Restoration

3.3.1 Summary of Restoration Investments

Over the past decade, 102 restoration projects across 53 coastal counties were funded by NOAA through the ARRA of 2009. Over half (62%, 63) of these restoration projects occurred in counties of the West Coast and Alaska regions, with most (42) of those occurring in California counties (Figure 13).

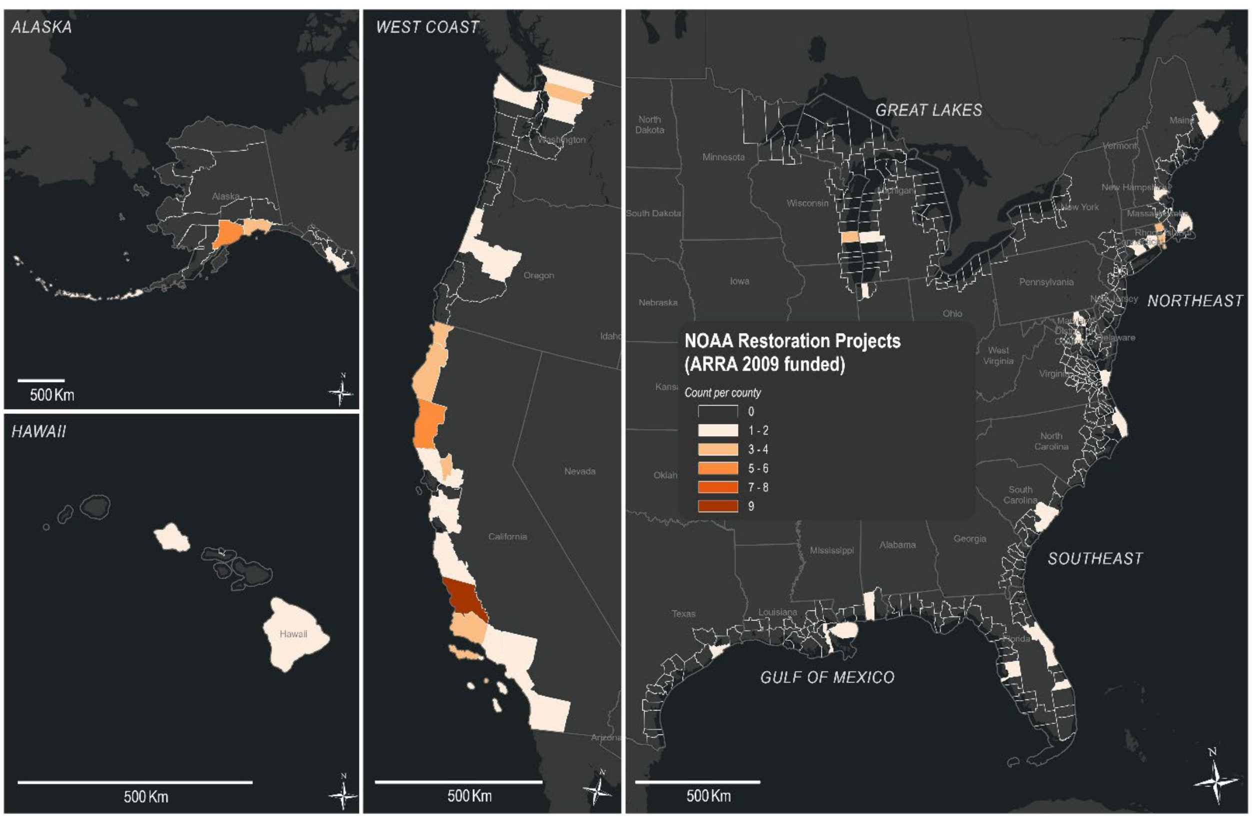


Figure 13. Map of the number of NOAA restoration projects funded by ARRA 2009 by county and region.

Among the coastal counties that received restoration investment, Alaska counties received the highest mean per capita investment in restoration ($21.10), followed by counties on the West Coast ($6.09) and in Hawaii ($3.57) (Figure 14). The five counties that received the highest amount of per capita investment were: 1) Aleutians West Census Area, Alaska ($194); 2) Prince of Wales-Hyder Census Area, Alaska ($177); 3) Northampton County, Virginia ($176); 4) Chugach Census Area, Alaska ($151); and 5) Dare County, North Carolina ($135).

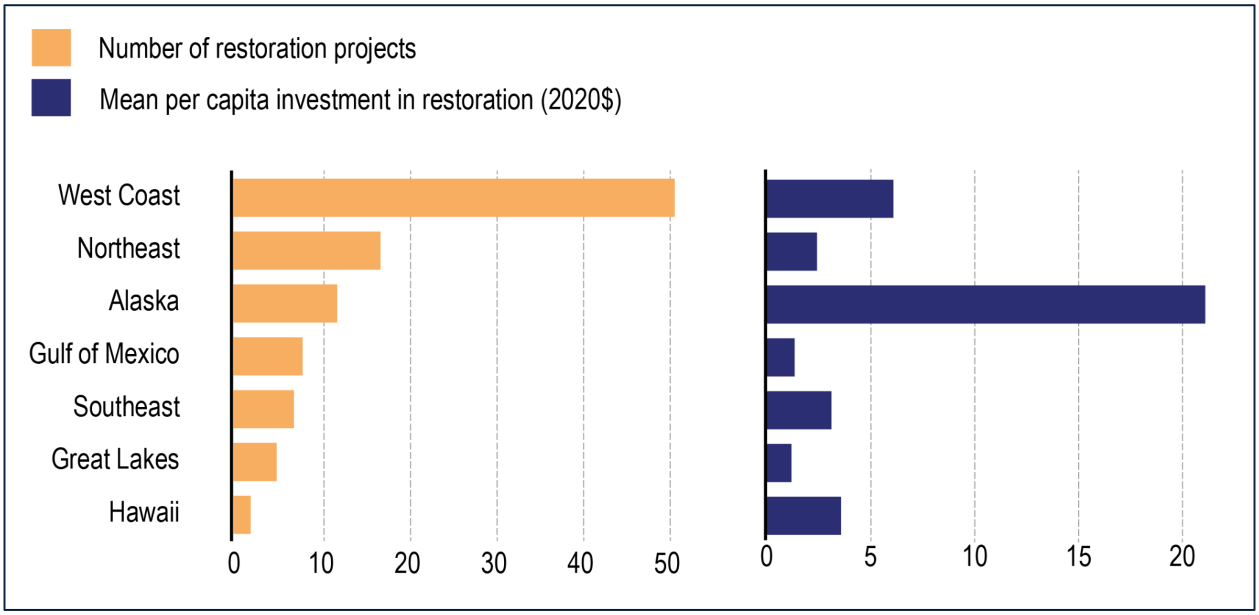
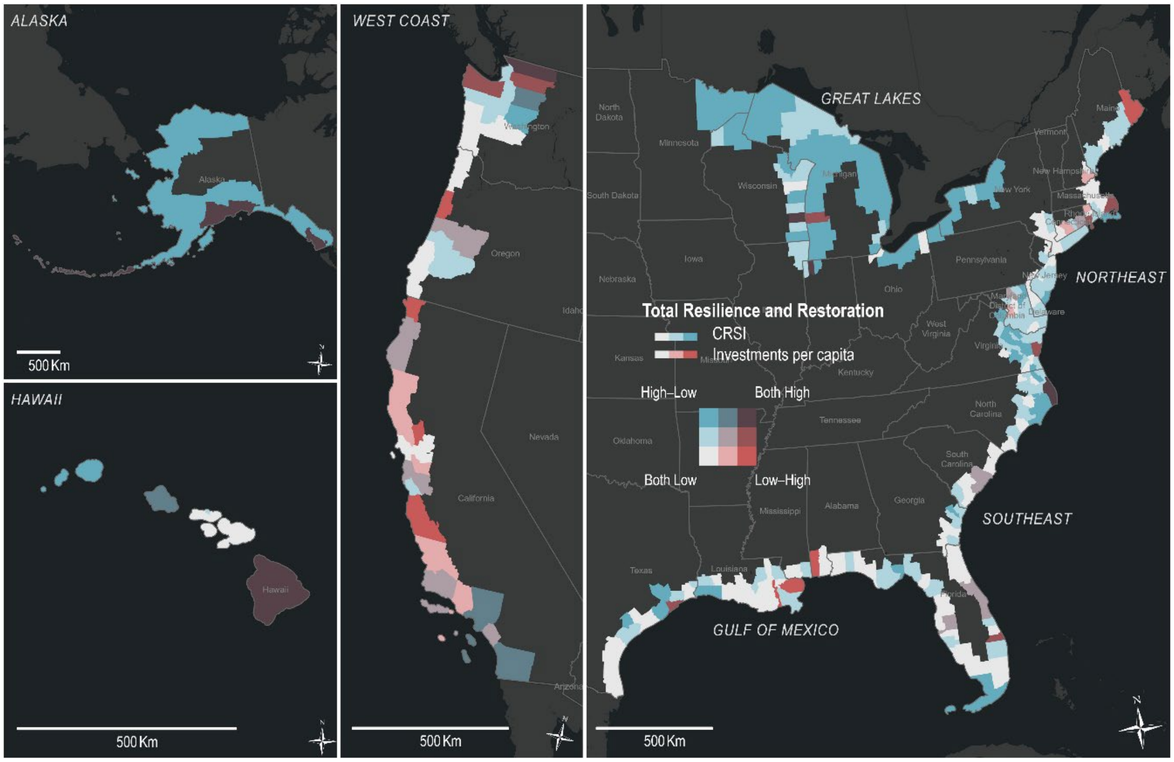


Figure 14. The number of ARRA 2009–funded NOAA restoration projects (orange) and the mean per capita investment of those projects (blue) by region, in 2020 dollars.

3.3.2 Restoration Investments and Resilience

Figure 15 displays the spatial overlap between CRSI (Figure 15a) and BRIC (Figure 15b) total resilience and restoration investments per capita. These maps highlight counties in gray in which investments per capita and total resilience scores were both low, representing counties in which future restoration investments could potentially support communities in need. For CRSI, these counties are primarily seen in the Pacific Northwest and throughout the Gulf of Mexico and East Coast (Figure 15a). A similar pattern is seen in the overlap with BRIC, where lower values appear in the Northwest and eastern Gulf of Mexico (Figure 15b).

(a)



(b)

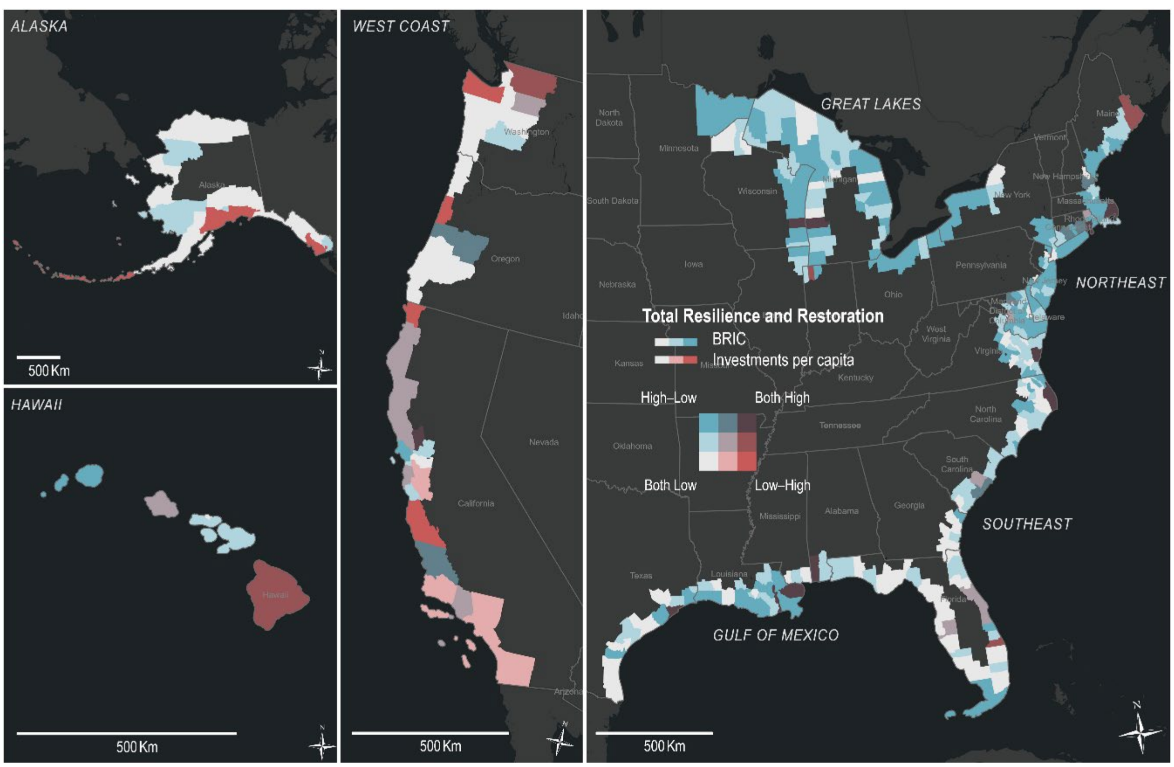


Figure 15. Bivariate choropleth maps of the intersection between (a) CRSI total resilience and ARRA restoration investments per capita and (b) BRIC total resilience and ARRA restoration investments per capita. Counties highlighted in gray indicate areas where investments per capita were zero and resilience scores were low.

Weak correlations, however, were found for both the number of restoration projects and per capita investments with all the resilience metrics, and no significant relationships were found across BRIC measures (Figure 16). This suggests that there is no relationship between restoration investments and resilience within this study's parameters.

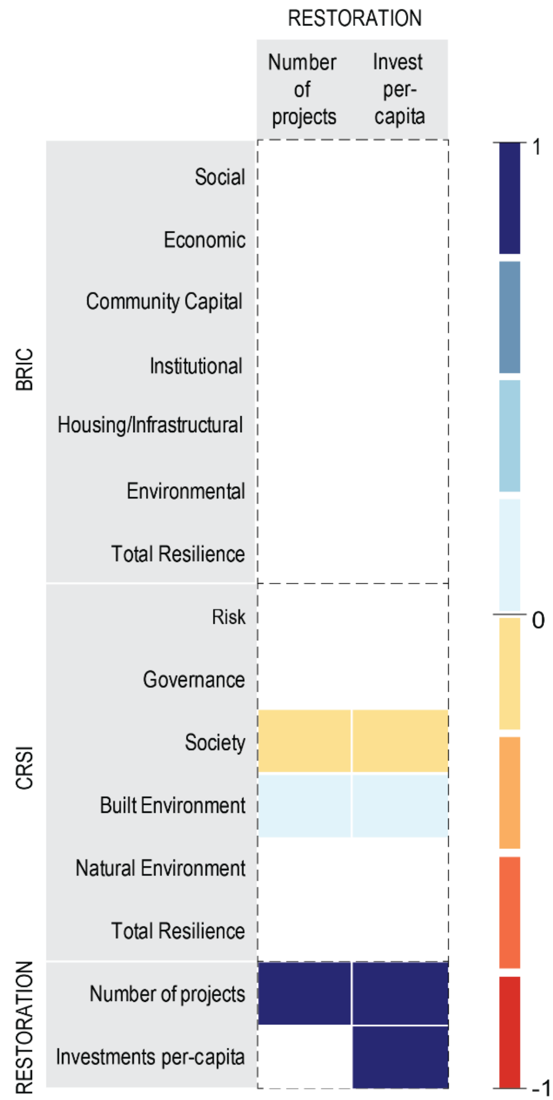


Figure 16. Spearman's rank correlation matrix between resilience measures and NOAA restoration projects funded by ARRA 2009. Color indicates the intensity of rho values and whether the relationship is direct (blue) or indirect (red). Only significant correlations (p < 0.01) are shown.

However, the Wilcoxon rank sum test of medians indicates that counties that received funding for at least one restoration project had significantly higher resilience according to BRIC's Social domain and CRSI's Built Environment domain as compared to counties that did not receive any restoration investments. On the contrary, counties that did not receive restoration funding were more resilient in terms of CRSI's Society domain. Given the number of counties that received zero restoration investments, this is the most important comparison in examining these data.

Chapter 4: Conclusions and Applications

The goals of this study were to: 1) identify a quantitative approach to measuring resilience in coastal communities, 2) analyze patterns of resilience, and 3) understand how patterns of resilience relate to investments in restoration and disaster recovery. As this was an exploratory study, key issues and challenges in quantifying a complex concept such as resilience surfaced throughout this exercise. These issues and challenges are presented below along with suggested solutions and future directions for the larger portfolio of work.

4.1 Interpretation of Results

Resilience is a word that has come to mean many things across disciplines and contexts, and how one defines resilience requires specifying resilience *of whom* and *to what* (Cutter, 2016a). This study, as well as the portfolio of work at NCCOS it falls within, was applied within the context of the resilience of coastal communities to natural hazards (NOAA National Ocean Service, 2016). The scientific literature offered a large menu of options for measuring resilience in different contexts and at varying levels of complexity (Cutter, 2016a; Koliou et al., 2018). For this coastal context, two of the relatively complex, secondary data-based approaches emerged as the most applicable for consideration. BRIC and CRSI shared a theoretical approach of using indicators across different domains to address resilience, and several of these domains shared individual indicators and data sources. This was especially true for the Social domains, where both relied on data derived from the U.S. Census Bureau, in particular, their ACS datasets. Yet, CRSI characterized resilience in an approach that required over 100 individual measures, including those that accounted for a community's risk to acute natural hazards. BRIC was constructed of 49 individual measures and instead was intended to capture a community's inherent resilience set apart from risk of hazard impacts. These differences in definition and application drove differing scores between CRSI and BRIC, as expected.

The two indices tell a similar story with the domains that relied on similar data, such as the Social domains. However, the indices tell different stories with regard to their overall total resilience scores because the domains that differed between the indices also had heavy influence on the overall score. This ultimately was due to the slightly different definition of resilience used in each of the frameworks. For example, the CRSI Risk domain highlights many parts of the country that are at high risk of floods and wildfires but relatively low in social resilience, meaning they have very low resilience overall. Conversely, for some areas with high risk and high resilience, CRSI ranked the overall resilience as medium. CRSI was meant to be a one-step overview of areas that need the most attention from programs designed to increase resilience and adaptive capacity. On the other hand, BRIC did not include risk at all but was instead often implemented alongside a risk map to identify areas in need (Derakhshan et al., 2022b). Even when BRIC was compared to a sum of CRSI's non-risk domains, each index highlighted different areas of the country as high or low resilience. The removal of risk shifted the West Coast results the most. While these two frameworks fit within the same realm of community resilience to natural hazards, how they defined "total resilience" differs, and the two cannot be viewed as comparable applications.

If different domains rank a county's resilience differently, then the question arises of how many domains or factors are necessary when evaluating resilience. In other words, how much complexity in a resilience assessment is necessary for a given context or research purpose? Depending on the intended use of the information or management need, a framework with too little complexity may be unable to capture the nuance required to represent resilience. The U.S. Census Bureau's CRE would be classified by many other researchers as a metric for vulnerability, but since it does not account for social capital, a factor that might be helpful in recovering from a disaster, CRE is not complex enough to truly account for resilience within some applications. Alternatively, even though the additional domains captured by CRSI, as compared to BRIC, proved important in characterizing resilience across communities, it is challenging to find the necessary data in every geography and across time.

Therefore, the added explanation provided by the numerous indicators brings with it questions of how to deal with missing data, especially if comparing across places or times with differing data availability. It also comes at a cost of ease of explanation of results, and as a result, some tools like CRE and the White House Council on Environmental Quality's (CEQ) new environmental justice screener are leaning toward slimmer indices with individual values evaluated by thresholds, rather than in aggregate (CEQ, 2022). The appropriate level of complexity will therefore be determined by research context and need.

The resilience indices tell a consistent story when compared to where disasters occur and restoration money is invested. Counties with high built infrastructure and housing scores in either index tended to be more resilient across both indices. This makes sense, as infrastructure (and the people associated with it) is what receives attention (i.e., disaster declarations and financial assistance, but also media stories) after a natural hazard event such as a hurricane. These areas are also more likely to have higher tax bases and localized expertise and therefore more sophisticated resources to invest in resilience and securing disaster aid. Declared disaster areas receive assistance in rebuilding said infrastructure, and restoration investments are often made with a goal of protecting said infrastructure. As a time series of infrastructure is particularly difficult, the order of cause and effect is unclear: are investments a driver of increased resilience, is high resilience a driver of attention and investments, or is it a combination of both? Importantly, however, this is only one aspect of resilience, and the Social and Community domains of each index often had an inverse relationship. Perhaps this is due to relative inattention to those aspects of a community in a disaster context, both because good data on these concepts are harder to find, and impacts to nontangible domains are less visible in the aftermath of a disaster. Either way, there is no official tracking of resilience metrics around disasters and no qualifications required for restoration funds related to any form of community resilience.

An assessment of the statistical and spatial relationships between resilience, disaster aid, and restoration funding can provide insight into how future resources could be prioritized. For example, areas with high disaster declaration rates and low CRSI resilience are potential areas to target for future studies to better understand what adaptations can directly contribute to resilience during the recovery period. Low CRSI scores are not uniformly caused; some counties scored low across the board, while others had moderate scores in some areas. So restoration investments might be targeted toward the areas in which counties scored the lowest. In another example, areas with low restoration investments and low BRIC resilience might be used to target future restoration efforts and/or future studies about the efficacy of that restoration. The restoration funding data presented here are representative only of NOAA-funded projects via the ARRA of 2009 because of its national coverage, but the majority of restoration funding is regionally focused (e.g., RESTORE Act in the Gulf of Mexico); future studies could determine if the relationships found in the national study hold true at smaller geographic scales.

4.2 Challenges

The concept of resilience implies tracking status over time to observe whether a community can recover from disturbance or whether interventions increase resilience capacity. While many of the resilience measures in the literature, including the two focused on in this study, implemented this by using indicators of what might best be called *capacity for resilience*, the need for data across time remains. However, one of the largest challenges in utilizing both CRSI and BRIC arose from lack of data availability, especially looking backward in time. The original CRSI was developed in 2017 using the most recently available data from 2015. BRIC was originally published in 2014 using data available in 2010 and before, and updates have been made with each incarnation. As described in the Methods section, both required updating with 2020 data, and both required alternative data sources for several indicators.

Therefore, calculations of individual indicators varied from the original methods, partly due to lack of sufficient documentation, and therefore domain scores should not be compared to the original nationwide dataset. Comparison would be possible for individual measures where direct updates were possible. In a head-to-head comparison between the HVRI nationwide BRIC values and the NCCOS-replicated coastal BRIC values, the top resilience counties were different. Differences most likely arose from the switch in several data inputs and/or through the cleaning and processing of those datasets before final inclusion in the index. Importantly, HVRI has also altered their methods before the 2020 data release and made several different decisions in those adaptations than the NCCOS team did. Replicability and comparability of these indices is therefore an issue, especially when one hopes to compare existing and newly compiled data across geographies or scales.

While some data sources were no longer accessible, several other sources changed how data were reported; this poses additional challenges in comparability across time. Data were also frequently delayed or missing for sparsely populated counties in the conterminous U.S., especially for Alaska and Hawaii. In addition, most data sources did not archive data before 2010 in easily accessible places; this is especially true for data sources like those from the U.S. Census Bureau that have collections extending much further back in time. This is likely due to web infrastructure advancements in 2010, and some data may be archived but not discoverable. Finally, some data sources, especially those in the Built Infrastructure domains, are continuously updated but not time stamped. For example, power plants are cataloged in a database as they are built and removed when they are decommissioned, but archived lists are not maintained.

A common challenge across the literature, as noted by Camacho et al. (2023), is the handling of missing data. This challenge is compounded when spatial and temporal scales of analysis are expanded and data become more inconsistent. The documentation for CRSI details how missing values for each input dataset should be handled; the available literature for BRIC does not (though BRIC authors confirmed their missing data protocols have changed over time). For some indicators, a zero is implied (i.e., if no power plants are listed for a county, it is reasonable to assign that value a true zero), while for others, missing data should be classified as “not available” and therefore sometimes dropped from statistical analysis. Either way, how missing values are handled can cause discrepancies in index values as the input measures are normalized and scaled relative to the study area (in this case, coastal counties). Index scores likely fail to accurately represent community resilience in locations such as Alaska and Hawaii where there is a significant proportion of data that is missing. CRSI resilience scores in Alaska ranked high, for instance, but an entire sub-domain of measures was missing; this likely explains why statistical outliers were observed for the majority of scores for Alaska.

All of these challenges result from the relative complexity of these indices, leading to an elevated need for data comparable in scale and resolution for index creation. Some examples such as the CRE and the CEQ Climate and Environmental Justice Screening Tool (CEQ, 2022) instead focused on a handful of indicators, treated individually, as a way to identify areas in need of additional attention. BRIC's related index, SoVI, was also found to be a good predictor of how recovery funds were distributed in South Carolina and was suggested to be a useful tool for expediting funds to those who need it most without the need for applicants to self-identify as vulnerable (Blackwood and Cutter, 2023). This suggests that perhaps a discrete metric addressing only some aspects of resilience may be sufficient.

4.3 Future Directions

This comparison of existing resilience frameworks is intended to serve as a first step in the study of community resilience for NCCOS, aiding researchers in efficiently characterizing resilience in coastal communities across the country. Findings suggest that further in-depth research, possibly including primary or qualitative data collections, would be beneficial in some regions or individual counties. As highlighted earlier, the goals of future research should dictate what measures are most applicable. For the NCCOS Vulnerability Assessment Portfolio, this might come in the form of a full, place-based vulnerability assessment. In these cases, a smaller-scale indicator approach can highlight dynamics and needs in particular neighborhoods, which is the scale at which adaptation projects often occur. In addition, place-based approaches can direct attention to the aspects of resilience most valued by the community.

CRSI and BRIC each highlight different counties as highest and lowest resilience. Comparisons between these rankings across each framework might uncover which aspects of resilience are important for further study. For example, some counties scored low on CRSI and high on BRIC because their Risk domain indicated low resilience; these areas might benefit most from risk reduction programs. A difference in the social capital component measures included in BRIC, compared to CRSI, could also explain opposing scores across the indices. The purpose of a national-scale study like this one might then be to situate place-based studies in a broader context. This can help ensure that place-based studies are implemented in places they might provide the most benefit. There is a dichotomy between context-sensitive resilience frameworks and the need for national-scale science, such as the mission of NCCOS. Frameworks, such as the ones explored within this study, may be able to bridge that tension.

Moving forward, as data management practices change and new data sources become available, each measure's construction can be reconsidered. For example, BRIC included data about telephone and internet connectivity of all speeds, while CRSI focused solely on broadband internet connection, which is rapidly becoming considered a necessary utility in the U.S. For smaller-scale studies, different and better data may be available, either in level of detailed information or in spatial resolution. Local customization of these types of indices is important as it can better reflect the values and concerns of the residents within the study area. BRIC has been adapted in such a way many times with success (Derakhshan et al., 2022b; Javadpoor et al., 2021; Scherzer et al., 2019). Within this study, BRIC and CRSI were both calculated according to their original methodologies, and along with a local or coastal adaptation process, they should also be subjected to sensitivity analyses within the context of coastal hazards. First among these would be to test how the indices respond to different imputation methods for missing data (especially for CRSI, which had more significant data gaps), to find a way to provide data for all geographies in a study.

This study was originally designed to explore how the NCCOS Vulnerability Assessment Portfolio of research can move beyond vulnerability into questions of resilience, to answer stakeholders' questions framed as, "We know we're vulnerable…now what?" The increased complexity of resilience frameworks brings added power to a secondarily sourced, indicator-based analysis, both statistically and in the ability to address more concepts. Due to NOAA's wide research responsibility, both in terms of geography and subject matter, there is not necessarily a "best fit" resilience framework. Regardless, the resilience frameworks, in some form, will serve as helpful screener tools to equitably decide where to complete more in-depth studies of vulnerability, resilience, and adaptive capacity.

As discussed initially within this report, vulnerability and resilience share some overlapping yet inversely related measures. As such, some measures of resilience could be incorporated into a standard vulnerability assessment alongside similar concepts in their thematic domain. Not all resilience and vulnerability measures can be utilized this way, however, and future assessments should not assume that highly resilient communities are not vulnerable (and vice versa). In addition, social capacity was one of the few concepts that was shown to be important across both resilience frameworks and consistently important across different geographies. Social capacity is just one aspect of adaptive capacity overall, the third concept in the broader study of natural hazards and how people respond to them. This makes sense as social capacity can directly provide the resources necessary for a community to recover from a hazard and might be an important domain to consider alongside vulnerability to directly address the question of what is next.

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Appendix A: Literature Review Spreadsheet

Table A1. Literature review spreadsheet.

Full Name	Year Published	Citation	Status
ARUP City Resilience Framework	2016	ARUP International Development and The Rockefeller Foundation, 2016	Implemented
ARUP International Development - Community Based Disaster Risk Reduction Study: Characteristics of a Safe and Resilient Community	2011	ARUP International Development and IFRC, 2011	Conceptual
Measuring Disaster Impact on Household Living Conditions: The Domestic Assets Approach	1992	Bates and Peacock, 1992	Conceptual
A Cross-Cultural Household Level-of-Living Scale	1972	Belcher, 1972	Conceptual
CGIAR Resilience Conceptual Framework	2016	Béné et al., 2016	Conceptual
Resilience in Lagoon Social-Ecological Systems	2005	Berkes and Seixas, 2005	Conceptual
An Operational Framework for Tracking Adaptation and Measuring Development (TAMD)	2013	Brooks et al., 2013	Conceptual
The Community Resilience Manual: A Resource for Rural Recovery and Renewal	2000	Centre for Community Enterprise, 2000	Implemented
Canterbury Wellbeing Index Summary 2016	2016	Canterbury District Health Board, 2016	Implemented
Community & Regional Resilience Institute Community Resilience System	2017	Plodinec, 2020	Conceptual
Inter-American Development Bank Disaster Deficit Index (DDI)	2005	Cardona et al., 2008	Conceptual
CGIAR Ecosystem Services and Resilience Framework	2014	Attwood et al., 2014	Conceptual
Building Community Resilience to Disasters (RAND)	2010	Chandra et al., 2011	Conceptual
Self-evaluation and Holistic Assessment of Climate Resilience of farmers and pastoralists framework (SHARP)	2015	Choptiany et al., 2015	Implemented
Constas and Barrett's Principles of Resilience Measurement for Food Insecurity (Constas and Barrett)	2013	Constas et al., 2013	Conceptual
Baseline Resilience Indicators for Communities (BRIC)	2014	Cutter et al., 2014; Derakhshan et al., 2022b (downscaled)	Implemented
Social Vulnerability Index (SoVI), Cutter et al.	2003	Cutter et al., 2003	Conceptual / Implemented
UK Department for International Development Building Resilience and Adaptation to Climate Extremes and Disasters framework (BRACED)	2014	McOmber et al., 2019	Conceptual
NOAA community well-being assessment method	2013	Dillard et al., 2013	Implemented
Assessments of Impacts and Adaptations of Climate Change (AIACC) Sustainable livelihood approach	2005	Osman-Elasha, 1980	Implemented
Hazus-MH	2017	Schneider and Schauer, 2006	Implemented
Constructing a Resilience Index for the Enhanced Critical Infrastructure Protection Program	2010	Fisher et al., 2010	Conceptual
Technical Assistance to NGO's (TANGO) Livelihood Framework	2002	Frankenberger et al., 2002	Conceptual

Full Name	Year Published	Citation	Status
Building Resilience in Rural Communities Toolkit	2008	Hegney et al., 2008	Conceptual
Resilience Capacity Index	2017	Institute of Governmental Studies, The University of California Berkeley, 2017 [deprecated online tool]	Conceptual
IASC In-Country Team Self-Assessment Tool for Natural Disaster Response Preparedness	2005	IASC, 2005	Not Clear
Operationalizing Resilience against Natural Disaster Risk: Opportunities, Barriers, and a Way Forward	2014	Keating et al., 2014	Conceptual
Capital-Based Approach to Community Disaster Resilience	2007	Mayunga, 2007	Conceptual
ResilUS: A Community Based Disaster Resilience Model	2011	Miles and Chang, 2011	Conceptual
Measuring Resilience and Vulnerability in U.S. Counties	2016	Miller et al., 2016	Implemented
Coastal Community Resilience: Building Resilience from the Inside Out	2011	National Preparedness Training Center, 2011	Conceptual
Community Resilience as a Metaphor, Theory, Set of Capacities, and Strategy for Disaster Readiness	2008	Norris et al., 2008; adapted by Sherrieb (2010) for publicly available data	Conceptual
The Resilience Adaptation and Transformation Assessment Framework (RATA)	2015	O'Connell et al., 2015	Implemented
The Oregon Resilience Plan: Reducing Risk and Improving Recovery for the Next Cascadia Earthquake and Tsunami	2013	OSSPAC, 2013	Implemented
Coastal Disaster Resilience Index	2010	Mayunga and Peacock, 2010	Conceptual
Communities Advancing Resilience Toolkit (CART): The CART Integrated System	2013	Pfefferbaum et al., 2013	Conceptual
THRIVE: Tool for Health & Resilience in Vulnerable Environments	2003	Prevention Institute, 2003	Implemented
Integrating Social Science into the Long-Term Ecological Research (LTER) Network: Social Dimensions of Ecological Change and Ecological Dimensions of Social Change	2004	Redman et al., 2004	Conceptual
Economic Resilience to Disasters: CARRI Research Report 8	2007	Rose, 2007	Conceptual
The Resilient City: Defining What San Francisco Needs from its Seismic Mitigation Policies	2009	SPUR, 2009	Implemented
Coastal Resilience Index "On the road to coastal resilience" A Community Self-Assessment: Understanding How Prepared Your Community is for a Disaster	2010	Sempier et al., 2010	Implemented
IFRC Framework for Community Resilience	2018	IFRC, 2018	Conceptual
Characteristics of a Disaster Resilient Community	2007	Twigg, 2007	Conceptual
Characteristics of a Disaster-Resilient Community	2009	Twigg, 2009	Conceptual
International Institute for Sustainable Development's Climate Resilience and Food Security (IISD)	2013	Tyler et al., 2013	Conceptual
Rockefeller Foundation's Asian Cities Climate Change Resilience Network (ACCCRN)	2014	Optiz-Stapleton et al., 2009	Implemented
Mitigation Framework Leadership Group (MitFLG) Draft Concept Paper: Draft Interagency Concept for Community Resilience Indicators and National-Level Measures	2016	DHS, 2016	Conceptual
How Resilient Is Your Coastal Community? A Guide for Evaluating Coastal Community Resilience to Tsunamis and Other Hazards	2007	Courtney et al., 2007	Conceptual

Full Name	Year Published	Citation	Status
Community Based Resilience Analysis (CoBRA)	2014	UNDP Drylands Development Centre, 2014	Conceptual
UNDRR Disaster Resilience Scorecard for Cities	2015	UNDRR, 2015	Implemented
Hyogo Framework of Action 2005–2015: Building the Resilience of Nations and Communities to Disasters	2007	UNISDR, 2007	Conceptual
A Global Report: Reducing Disaster Risk, a Challenge for Development	2004	UNDP, 2004	Conceptual
World Risk Index	2014	UNU-EHS, 2014	Implemented
USAID Measurement for Community Resilience	2013	USAID, 2013	Conceptual
Feinstein International Center's Livelihood and Resilience Framework (Feinstein)	2017	Maxwell et al., 2017	Conceptual
Resilient Washington State: A Framework for Minimizing Loss and Improving Statewide Recovery after an Earthquake	2012	Washington State Emergency Management Council: Seismic Safety Committee, 2012	Implemented
Population and demographics, Environmental and ecosystem, Organized governmental services, Physical infrastructures, Lifestyle and community competence, Economic development, and Social-cultural capital	2021	Cimellaro et al., 2016; Cardoni et al., 2021; Renschler et al., 2010; De Iuliis et al., 2022	Implemented
Empirical Evidence Resilience Index	2021	Feldmeyer et al., 2021	Implemented
Community Intrinsic Resilience Index	2021	Gerges et al., 2022	Implemented
time-to-recovery and magnitude of impact of human mobility data	2021	e.g., Hong et al., 2021; Podesta et al., 2021	Implemented
Analysis of Resilience of Communities to Disaster	2022	Islam et al., 2022	Implemented
Cumulative Resilience Screening Index	2022	Summers et al., 2020; validated by Summers, 2022	Implemented
Resilience to Emergencies and Disasters Index	2018	Kontokosta and Malik, 2018	Implemented
Resilience Inference Measurement	2016	Lam et al., 2016	Implemented
A Validation of Metrics for Community Resilience to Natural Hazards and Disasters Using the Recovery from Hurricane Katrina as a Case Study	2015	Burton et al., 2015	Implemented
Ecosystem services-based composite indicator for assessing community resilience to floods	2018	Abenayake et al., 2018	Implemented
Resilience Analysis and Planning Tool (RAPT)	2020	Edgemon et al., 2020	Implemented
Australian National Disaster Resilience Index (ANDRI)	2020	Parsons et al., 2017	Implemented
Community Resilience Index (CRI2)	2010	Sherrieb et al., 2010	Implemented
Disaster Resilience of Place (DROP)	2010	Cutter et al., 2010	Conceptual
Bec et al., 2019	2019	Bec et al., 2019	Conceptual
Rural Resilience Index (RRI)	2015	Cox and Hamlen, 2015	Conceptual
Tract-level Baseline Resilience Indicators for Communities	2022	Derakhshan et al., 2022b	Implemented
Community Resilience Estimates	2019	US Census Bureau, 2024	Implemented

Appendix B: CRSI and BRIC Detailed Indicator Descriptions

Table B1. CRSI detailed indicator descriptions.

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Built Environment	Communication Infrastructure	cell service towers	count of cell service towers	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		internet service access	percent of homes with access to internet service provider(s)	2023	National Broadband Map Datasets https://www.broadbandmap.gov/analyze		zero	percentage of homes for broadband serviceable locations for which providers report residential fixed broadband service with any technology and speeds of at least 25 / 3 Mbps
		land mobile broadcast towers	count of land mobile broadcast towers	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		microwave service towers	count of microwave service towers	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		paging transmission towers	count of paging transmission towers	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		radio broadcast transmission towers	count of FM broadcast towers	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/	Y	zero	summarize within
		TV station transmitters	count of TV station transmitters	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
	Housing Characteristics	housing density	housing units per square mile	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	divide total houses by area in sq mi
		homes with inadequate plumbing and kitchen facilities	percent of houses without adequate plumbing and kitchen facilities	2016–2020	Comprehensive Housing Affordability Strategy https://www.huduser.gov/portal/datasets/cp/CHAS/data_querytool_chas.html		zero	sum of owners + renters without complete bathroom and kitchen facilities, divided by total houses

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Built Environment (cont.)	Housing Characteristics (cont.)	home crowding	percent of houses with more people than rooms	2016–2020	Comprehensive Housing Affordability Strategy https://www.huduser.gov/portal/datasets/cp/CHAS/data_querytool_chas.html		zero	Number of Houses with >1.5 people per room, sum of both owners and renters, divided by total houses
		median age of residential housing	median age of residential housing	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	2020-year built
		mobile homes	percent of housing that is non-permanent or mobile, excluding vans, campers, etc.	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	mobile/total housing units
	Transportation Infrastructure	airports	counts of airports	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		helicopter transport	counts of helipads	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		highway access	highway access points per 10,000 people	2023	U.S. Geological Survey (USGS). (2023). National atlas. https://www.usgs.gov/programs/national-geospatial-program/national-map	Y	zero	[Number of road egress points / County population] * 10,000
		freight rails	miles of operating freight rails	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		roadway bridge structural and functional assessment rating	mean assessment rating	2020	National Bridge Inventory https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm		null	summarize within for Structural_eval_067
		roadway bridge structures	count of bridges	2020	National Bridge Inventory https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm		zero	summarize within
		seaplanes	count of seaplane landing areas	2023	Homeland Infrastructure Foundation-Level Data https://hifld-geoplatform.opendata.arcgis.com/		zero	summarize within
		roadway availability	total miles of urban and rural arterial roads	2023	https://www.fhwa.dot.gov/planning/processes/tools/nhpn/index.cfm		zero	FCLASS = 2, 6, 14, or 16; summarize within

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Built Environment (cont.)	Transportation Infrastructure (cont.)	power generating facilities	count of power generating facilities	2023	United States Energy Information Administration https://atlas.eia.gov/datasets/power-plants/explore?location=41.629235%2C-118.496000%2C3.82		zero	summarize within
		public drinking water supply facilities	public drinking water supply facilities	2023	https://www.epa.gov/ground-water-and-drinking-water/safe-drinking-water-information-system-sdwis-federal-reporting		zero	sum of the number of facilities in each county
		wastewater treatment facilities	wastewater treatment facilities	2023	Enforcement and Compliance History Online https://echo.epa.gov		zero	pivot table for count of facilities per FIPS for both biosolids and stormwater, sum
	Vacant Structures	vacant business structures	percent of business structures that are vacant	2020	United States Postal Service https://www.huduser.gov/portal/datasets/usps.html		zero	join to tract polygons, summarize within counties, divide vacant by total
		vacant residential structures	percent of residential structures that are vacant	2020	United States Postal Service https://www.huduser.gov/portal/datasets/usps.html		zero	join to tract polygons, summarize within counties, divide vacant by total
		vacant structures that are not identified as business or residential	percent of "other" structures that are vacant	2020	United States Postal Service https://www.huduser.gov/portal/datasets/usps.html		zero	join to tract polygons, summarize within counties, divide vacant by total
Governance	Community Preparedness	Community Rating System class designation	Community Rating System class designation average score	2020	Federal Emergency Management Agency https://www.fema.gov/flood-insurance/work-with-nfip/community-status-book		null	average communities in county
		recovery funds spent on hazard mitigation	Small Business Administration recovery funds spent on hazard mitigation	2020	https://data.sba.gov/dataset/disaster-loan-data		zero	sum total loans for business claims by zip, crosswalk to county, and sum
	Natural Resource Conservation	Land Protection Priority Index for preserving biodiversity	Land Protection Priority Index for preserving biodiversity*	2017	https://biodiversitymapping.org/index.php/download/	Y	null	summarize within for Priority Index Summary
	Personal Preparedness	homes with mortgages	percent homes with mortgages (which assumes insurance coverage).	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	Owner-occupied units / owner-occupied units with a mortgage/total homes
		National Flood Insurance Program community participants	% housing units covered by National Flood Insurance Program	2023	Federal Emergency Management Agency https://www.fema.gov/data-feeds	Y	zero	[Residential NFIP policy holders / Number of housing units] * 100

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Natural Environment	Condition	biodiversity	biodiversity based on avian taxa richness	2017	https://biodiversitymapping.org/index.php/download/		null	none
		clean air days	Sum of days AQI rated as Good and Moderate, divided by Total days with AQI data	2020	U.S. Environmental protection Agency https://www.epa.gov/outdoor-air-quality-data/air-quality-index-report		zero	(good days + moderate days) / total AQI days
	Environment	Soil Productivity Index	average Soil Productivity Index	2023	National Aquatic Resource Surveys: https://www.epa.gov/national-aquatic-resource-surveys	Y	null	zonal statistics mean
		Coastal Condition Score	average Coastal Condition Score across all 4 subject areas	2017	https://www.epa.gov/national-aquatic-resource-surveys		null	percent of index tests that turned up "good" within a 3-mile buffer of each county, averaged across all 4 subject areas
		Forest Condition Score	Forest Condition Score based on stand age and live basal area	2020	Forest Inventory and Analysis Database: https://apps.fs.usda.gov/fia/datamart/datamart.html	Y	null	combine states, sum of normalized STDAGE, BALIVE
		Lake Condition Score	Lake Condition Score	2017	National Aquatic Resource Surveys: https://www.epa.gov/national-aquatic-resource-surveys		null	percent of tested categories rated in the most favorable category; averaged across all sites in the county
		River Condition Score	River Condition Score	2017	National Aquatic Resource Surveys: https://www.epa.gov/national-aquatic-resource-surveys		null	percent of tested categories rated in the most favorable category; averaged across all sites in the county
		soil classified as suitable for farming	NCCPI score	2023	NCCPI: https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx		null	percent of the county with NCCPI score >0.5
		Wetland Condition Score	Wetlands Condition Assessment Score	2017	National Aquatic Resource Surveys: https://www.epa.gov/national-aquatic-resource-surveys		null	percent of sites classified as "good"
	Extent of Ecosystem Types	agricultural land cover	agricultural land cover		National Land Cover Database: https://www.mrlc.gov			reclass 81/82 to 1, everything else to 0, zonal statistics mean
		coastal water	percent of county classified as water		Census Cartographic Boundaries		zero	Awater/(Awater+ALand)
		forest cover	percent of county classified as forest	2019	National Land Cover Database: https://www.mrlc.gov		zero	reclass Deciduous, Evergreen, and Mixed forests as forest, zonal statistics

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Natural Environment (cont.)	Extent of Ecosystem Types (cont.)	freshwater cover	percent of county classified as water	2019	National Land Cover Database: https://www.mrlc.gov		zero	zonal statistics, for NLCD category 11 (Open Water)
		grassland cover	percent of county classified as grassland	2019	National Land Cover Database: https://www.mrlc.gov		zero	zonal statistics for NLCD category 71 (Grassland/Herbaceous
		ice cover	percent of county classified as ice or snow		National Land Cover Database: https://www.mrlc.gov		zero	zonal statistics, for NLCD category 12 (Perennial Ice/Snow)
		protected area cover	percent of county designated as protected	2022	U.S. Geological Survey (USGS) Gap Analysis Project (GAP). (2022). Protected areas database of the United States (PAD-US) 3.0: U.S. Geological Survey data release, https://doi.org/10.5066/P9Q9LQ4B		zero	summarize with (do not dissolve, so lands with two designations counted twice)
		tundra cover	percent of county classified as tundra (Alaska only)	2019	National Land Cover Database: https://www.mrlc.gov		zero	reclass NLCD categories 72 (Sedge/Herbaceous), 73 (Lichens), and 74 (Moss) into “tundra,” zonal statistics
		wetland cover	percent of county classified as wetland	2019	National Land Cover Database: https://www.mrlc.gov		zero	reclass NLCD categories 90 (Woody Wetlands) and 95 (Emergent Herbaceous Wetlands), zonal statistics
Risk	Exposure	basic hurricane exposure	percent of county affected by hurricane winds	2020	https://www.nhc.noaa.gov/data/tcr/index.php?season=2020&basin=atl		zero	percent of county affected by windswath radius layer of any storm
		basic tornado exposure	count of tornados recorded in county	2020	https://www.ncdc.noaa.gov/stormevents/ftp.jsp		zero	geocode (begin lat/begin lon) --> filter tornado --> summarize within
		coastal flooding exposure	percent of county in designated flood zones	2023	FEMA	Y	zero	merge state data -> select A and V zones -> summarize within
		drought exposure	amount of time county spent in drought status	2020	https://www.drought.gov/data-maps-tools/us-drought-monitor	Y	null	DSCI calculated by weighted sum of drought categories for weekly data, summed across the year
		earthquake exposure	percent of county at risk of damaging earthquakes	2023	https://www.usgs.gov/programs/earthquake-hazards/seismic-hazard-model-maps-and-site-specific-data	Y	null	select polygons in top 4 quantiles of PGA risk map (BC, 2% in 50 year risk) -> dissolve -> summarize within counties
		extreme high temperature exposure	count of high heat events recorded in county	2020	https://www.ncdc.noaa.gov/stormevents/ftp.jsp	Y	zero	filter by event type = excessive heat or heat, summarize within

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Risk (cont.)	Exposure (cont.)	extreme low temperature exposure	count of extreme cold events recorded in county	2020	https://www.ncdc.noaa.gov/stormevents/ftp.jsp	Y	zero	filter by event type = extreme cold/wind chill, summarize within
		hail exposure	count of hailstorms recorded in county	2020	https://www.ncdc.noaa.gov/stormevents/ftp.jsp		zero	filter by event type = hail, summarize within
		hurricane exposure	percent of county in a hurricane's radius	2020	https://www.nhc.noaa.gov/data/tcr/index.php?season=2020&basin=atl		zero	merge & dissolve radii into one layer -> percent of county affected by hurricane radii
		inland flooding exposure	percent of county in designated flood zones	2023	FEMA	Y	zero	merge state data -> select A and V zones -> summarize within
		landslide exposure	percent of county in landslide risk zone	2023	https://maps.nccs.nasa.gov/arcgis/apps/MapAndAppGallery/index.html?appid=574f26408683485799d02e857e5d9521		zero	summarize within
		nuclear exposure	proportion of land that falls in a 10-mile radius of nuclear facility	2023	referred to HIFLD by NRC	Y	zero	Filter nuclear -> Buffer (10 mi, Dissolve) -> Summarize Within -> Calculate Percent
		RCRA release exposure	proportion of land that falls in a 1/4 mile radius of a RCRA site	2020	RCRA raw data: https://rcrapublic.epa.gov/rcra-public-export/?outputType=CSV		zero	geocode -> buffer (.25mi, Dissolve) -> Summarize Within
		Superfund exposure	proportion of land that falls in a 5-mile radius of Superfund Site	2020	NPL boundaries: https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7BFC07D75C-8596-434B-B1A6-0688C9CD45B5%7D Listing dates: https://www.epa.gov/superfund/superfund-data-and-reports#archived (FOIA 4 and 5)		zero	Join dates to NPL buffer -> Filter by year -> Buffer (5mi) -> Dissolve -> Summarize Within -> calculate %
		tornado exposure	length of tornado tracks recorded in county	2020	https://www.spc.noaa.gov/gis/svrgis/		zero	summarize within: meters of tornado tracks in county
		Toxic Release exposure	Proportion of land that falls in a 1/4 mile radius of a TRI location	2020	TRI sites: https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-present		zero	Buffer (.25mi, Dissolve) --> Summarize Within -> calculate percent
		wildfire exposure	percent of county affected by wildfire	2020	https://www.sciencebase.gov/catalog/item/5ee13de982ce3bd58d7be7e7		zero	filter by all fires up to the given year -> summarize within -> summarized area/total area = FireExp

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Risk (cont.)	Exposure (cont.)	wind exposure	county of recorded high wind events in the county	2020	https://www.ncdc.noaa.gov/stormevents/ftp.jsp	Y	zero	number of reported high wind, strong wind, or thunderstorm wind (counting marine categories of each), summarize within
	Loss	loss of human life and property to natural hazards	count of reports of loss of life and property to natural hazards	2021	https://cemhs.asu.edu/sheldus		zero	Record: number of reports of hazards that caused loss of life or property
		loss of natural land to impervious surfaces	percent impervious surface change from 2011–2019	2019	https://www.mrlc.gov/data	Y	null	zonal statistics mean for each year, 2019-2011
		loss of natural land to impervious surfaces and crop land	percent agricultural land change from 2011–2019	2019	https://www.mrlc.gov/data	Y	null	reclass 81/82 to 1, everything else to 0, zonal statistics mean, 2019–2011
Society	Demographics	linguistic isolation	percent of population exhibiting limited English language skills	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	sum of Spanish speakers and Other Language speakers that do not speak English "very well" divided by total
		low education - 12th grade	percent of population age 25 years and over who attended high school but did not receive a diploma	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	2020: divide number of high school dropouts by total over 25
		low education - 9th grade	Percent of population age 25 years with less than 9th grade educational attainment	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	2020: divide number with <9th grade by total over 25
		elderly population	population age 65 or greater and living alone	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	divide number living alone by total population over 65
		very young population	population under 5 years of age	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	divide number under 5 by total
	Economic Diversity	economic diversity	metric of economic diversity based on NAICS codes	2023	https://www.chmura.com/download-diversity-index-county	Y	null	proprietary, but Hachman Index found here https://gardner.utah.edu/wp-content/uploads/HachmanBriefFinal.pdf?x71849

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Society (cont.)	Economic Diversity (cont.)	income inequality based on the Gini Index	Gini Index	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	none
	Health Indicators	adults living with asthma	percent of adult population diagnosed with asthma	2022	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none
		children living with asthma	percent of population under 18 diagnosed with asthma	2023	American Lung Association, https://www.lung.org/research/trends-in-lung-disease		null	used ALA summary for each state, joined by state ID
		diabetes	percent of population living with type 1 or type 2 diabetes	2022	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none
		heart disease	incidence of heart disease per 1,000 population	2022	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none
		stroke	incidence of stroke per 1,000 population	2022	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none
		obesity	percent of population diagnosed with obesity	2022	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none
		health insurance coverage	population with at least some health insurance coverage	2020	U.S. Census Bureau, ACS, S2701 Selected Characteristics of Health Insurance Coverage		null	none
		population with cognitive and/or physical special needs	population with cognitive and/or physical special needs	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	none
		prevalence of cancer in the population	percent of population diagnosed with cancer	2020	CDC, PLACES: https://chronicdata.cdc.gov/500-Cities-Places/PLACES-County-Data-GIS-Friendly-Format-2022-releas/i46a-9kgh	Y	null	none

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Society (cont.)	Labor and Trade Services	concrete construction services	concrete construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		construction framing services	construction framing services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		highway construction services	highway construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		masonry services	masonry services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		power construction services	power construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		roofing construction services	roofing construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		steel construction services	steel construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
		water and sewer construction services	water and sewer construction services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count of businesses by 100k population
	Safety and Security	criminal and civil services	criminal and civil services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_emplvl = total employees in the county/ total*100000
		emergency and civil services	emergency and civil services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	divide count by 100k population
		law enforcement officers	law enforcement officers per 100,000 population	2020	Federal Bureau of Investigation https://ucr.fbi.gov/		zero	average for each district within a county by matching county names (proper case, no "parish" or "county," ignoring shared officers listed in multiple counties)/100k
		other public safety services	other public safety services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_emplvl = total employees in the county/ total*100000

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Society (cont.)	Social Cohesion	ethnic isolation	degree of ethnic isolation based on calculated index: chances that two people in the area pulled at random are the same race	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates	Y	null	$DI = 1 - (H^2 + W^2 + B^2 + AIAN^2 + Asian^2 + NHPI^2 + SOR^2 + Multi^2)$ (Census 2010-2020 definition)
		born in state of residence	percent of population born in current state of residence	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		zero	divide by total population to get proportion
		religious congregation participation	religious congregation participation per 1,000 population	2020	US Religion Census; https://www.usreligioncensus.org/		zero	none
	Social Services	medically underserved areas	% of county in a medically underserved area	2023	Health Resources and Services Administration https://datawarehouse.hrsa.gov/	Y	zero	calculate by area and pop, % underserved
		medically underserved areas, mental health	% of county in a medically underserved area, mental care	2023	Health Resources and Services Administration https://datawarehouse.hrsa.gov/	Y	zero	calculate area %
		medically underserved areas, primary care	% of county in a medically underserved area, primary care	2023	Health Resources and Services Administration https://datawarehouse.hrsa.gov/	Y	zero	calculate area %
		blood and organ banks	blood and organ banks per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / by population *100000
		childcare services	childcare services per 100,000 population under 14	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / pop14U *100000
		emergency shelter, food, and goods services	emergency shelter, food, and goods services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population * 100000
		hospitals	hospitals per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm	Y	zero	annual_avg_estabs_count / population * 100000
		insurance claims establishments	insurance claims establishments per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population * 100000
		K-12 education and support facilities	K–12 education and support facilities per 100,000 population ages 5 to 18	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	sum of establishments / pop5to18 *100000

Domain	Subdomain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Society (cont.)	Social Services (cont.)	mental health support	mental healthcare facilities per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	sum of establishments / population * 100000
		social advocacy services	number of social advocacy services per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population * 100000
		outpatient and emergency facilities	outpatient and emergency facilities per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / by population *100000
		rehabilitative service facilities	rehabilitative service facilities per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population * 100000
		religious organizations	religious organizations per 100,000 population	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population * 100000
		special needs transportation services	special needs transportation services per 100,000 population with special needs	2020	QCEW: https://www.bls.gov/cew/downloadable-data-files.htm		zero	annual_avg_estabs_count / population with special needs* 100000
	Socio-economics	median household income	median household income in inflation adjusted dollars	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	none
		poverty	population living at or below 150 poverty threshold	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	convert to percent
		unemployment	unemployment rate of population ages 16 years and greater	2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		null	none

Table B2. BRIC detailed indicator descriptions.

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Social	educational attainment equality	negative absolute difference between % population with college education and % population with less than high school education	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	1 - [ABS{[Pct population Less than 9th grade + Pct population 9th to 12th grade, no diploma] - [Pct population some college, no degree +Pct population associate's degree + Pct population bachelor's degree or higher]]
Social	pre-retirement age	% population below 65 years of age	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates	Y	Null	100 - [Pct pop 65 years and over]
Social	transportation	% households with at least one vehicle	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct occupied housing units with 1 vehicle available
Social	communication capacity	% households with telephone service available	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	{[Owner occupied households with telephone service available + Renter occupied households with telephone service available]/Total households} * 100
Social	English language competency	% population proficient English speakers	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	[Pct population 5 years and over English only] + [Pct population 5 years and over other language - Speak English well]
Social	non-special needs	% population without sensory, physical, or mental disability	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	100 - [Percent with a disability - Total civilian noninstitutionalized population]
Social	health insurance	% population under age 65 with health insurance	2020	U.S. Census Bureau. (2020). Small Area Health insurance estimates (SAHIE). https://www.census.gov/data-tools/demo/sahie/#/		Null	Percent insured
Social	mental health support	psychosocial support facilities per 10,000 persons	2020	Bureau of Labor Statistics (BLS). (2020). Quarterly census of employment and wages. https://www.bls.gov/cew/downloadable-data-files.htm	Y	Zero	[Number mental health support facilities/County population]*10000
Social	food provisioning capacity	food security rate	2019–2021	Gundersen, C., Dewey, A., Crumbaugh, A., Kato, M., and Engelhard, E. (2023). Map the meal gap: A report on county and congressional district food insecurity and county food cost in the United States in 2019–2021. Feeding America.	Y	Null	1 - [Overall Food Insecurity Rate]

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Social (cont.)	physician access	physicians per 10,000 persons	2020	University of Wisconsin Population Health Institute. (2020). County health rankings & roadmaps 2020. www.countyhealthrankings.org	Y	Zero	[Count primary care physicians/County population] * 10000
Economic	homeownership	% owner-occupied housing units	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct occupied housing units owner-occupied
	employment rate	% labor force employed	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	{[Population 16 years and over in labor force employed]/[Population 16 years and over in labor force]} * 100
	income equality	negative Gini coefficient	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	1 - [Estimate!!Gini Index]
	non-dependence on primary/tourism sectors	% employees not in farming, fishing, forestry, extractive industry, or tourism	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	100 - {[Pct!!INDUSTRY!!Civilian employed population 16 years and over!!Agriculture, forestry, fishing and hunting, and mining] + [Pct!!INDUSTRY!!Civilian employed population 16 years and over!!Arts, entertainment, and recreation, and accommodation and food services]
	gender income equality	negative absolute difference between male and female median income	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Percent of absolute difference between male median annual earnings and female median annual earnings divided by annual income (Inverted)
	business size	ratio of large to small businesses	2020	U.S. Census Bureau. (2020). County business patterns. https://www.census.gov/programs-surveys/cbp/data/datasets.html		Null	Large (more than 100 employees) businesses / Small (fewer than 10 employees) businesses
	large retail-regional /national geographic distribution	large retail stores per 10,000 persons	2020	U.S. Census Bureau. (2020). County business patterns. https://www.census.gov/programs-surveys/cbp/data/datasets.html		Null	[Number large retail stores / Population] * 10,000
	federal employment	% labor force employed by federal government	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct civilian employed population 16 years and over government workers
Community Capital	place attachment - not recent immigrants	% population not foreign-born persons who came to US within previous five years	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	100 - [Foreign born (Entered 20xx or later (5 years) population]
	place attachment - native born residents	% population born in state of current residence	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct County population native born in US state of residence

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Community Capital (cont.)	political engagement	% voting age population participating in presidential election	2020	Leip, D. (2020). Detailed voter registration and turnout data, version 0.90.21. https://uselectionatlas.org/		Null	[Voting turnout / Total voting age county population] * 100
	social capital - religious organizations	persons affiliated with a religious organization per 10,000 persons	2020	Grammich, C., Hadaway, K., Houseal, R., Jones, D. E., Krindatch, A., Stanley, R., and Taylor, R. H. (2023). 2020 U.S. religion census: religious congregations & membership study. Association of Statisticians of American Religious Bodies. https://www.usreligion census.org		Null	[Religious organization adherents / County population] *10,000
	social capital - civic organizations	civic organizations per 10,000 persons	2020	U.S. Census Bureau. (2020). County business patterns. https://www.census.gov/programs-surveys/cbp/data/datasets.html		Zero	[Number civic organizations / Population] * 10,000
	place attachment - not recent immigrants	Red Cross volunteers per 10,000 persons	2021	AmeriCorps. (2023). Current population survey civic engagement and volunteering (CEV) supplement, 2021. Analytical version. AmeriCorps Office of Research and Evaluation. https://data.americorps.gov/Volunteering-and-Civic-Engagement/2021-CEV-Current-Population-Survey-Civic-engagemen/rgh8-g2uc	Y	Null	[Number of volunteers / County population] * 10,000
	social capital - citizen disaster preparedness and response skills	Red Cross training workshop participants per 10,000 persons	2020	Federal Emergency Management Agency. (2020). National household survey. https://www.fema.gov/about/openfema/data-sets/national-household-survey	Y	Null	[Number of workshop training participants / County population] * 10,000
Institutional	mitigation spending	10-year average per capita spending for mitigation projects	2023	Federal Emergency Management Agency. (2023). Hazard mitigation assistance projects. v.3. https://www.fema.gov/openfema-data-page/hazard-mitigation-assistance-projects-v3		Zero	10-yr avg spending for hazard mitigation projects / County population
	flood insurance coverage	% housing units covered by National Flood Insurance Program	2023	Federal Emergency Management Agency (FEMA). (2023). National flood insurance policies redacted policies. v.2. https://www.fema.gov/openfema-data-page/fima-nfip-redacted-policies-v2		Zero	[Residential NFIP policy holders / Number of housing units] * 100

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Institutional (cont.)	jurisdictional coordination	governments and special districts per 10,000 persons	2017	U.S. Census Bureau. (2017). Census of governments: Public use files. https://www.census.gov/programs-surveys/gus/data/orgpublicusefiles.All.List_1216629514.html#list-tab-List_1216629514		Zero	[Number of govts and special districts / County population] * 10,000
	disaster aid experience	presidential disaster declarations divided by loss-causing hazard events from 10-year time range	2023	CEMHS. (2023). Spatial hazard events and losses database for the United States (SHELDUS). Version 21.0. [online database]. Center for Emergency Management and Homeland Security, Arizona State University		Zero	Presidential disaster declarations / Loss-causing hazard events
	local disaster training	% population in communities with Citizen Corps program	2015	Federal Emergency Management Agency (FEMA). (2015). Community emergency response team (CERT) Dataset. https://www.fema.gov/about/openfema/data-sets/community-emergency-response-team-cert-dataset	Y	Zero	[Sum of population of block groups with CERT programs within county / County population] * 100
	performance regimes-state capital	proximity of county seat to state capital	2023	U.S. Geological Survey (USGS). (2023). National atlas. https://www.usgs.gov/programs/national-geospatial-program/national-map U.S. Census Bureau. (2020). Tiger/Line shapefiles. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2020.html#list-tab-790442341		Zero	Euclidean distance from county seat to state capital
	performance regimes-nearest metro area	proximity of county seat to nearest county seat within a Metropolitan Statistical Area	2023	U.S. Geological Survey (USGS). (2023). National atlas. https://www.usgs.gov/programs/national-geospatial-program/national-map U.S. Census Bureau. (2020). Tiger/Line shapefiles. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2020.html#list-tab-790442341		Zero	Euclidean distance from county seat to nearest MSA
	population stability	population change over previous five-year period	2020	U.S. Census Bureau. (2020). 2020 Census Redistricting Data.		Null	Population change over previous five-year period

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Institutional (cont.)	nuclear plant accident planning	% population within 10 miles of nuclear power plant	2022	Oak Ridge National Laboratory (ORNL). (2022). Power plants. https://hifld-geoplatform.opendata.arcgis.com/		Zero	[Sum of population of block groups within 10 miles of nuclear power plant within county / County population] * 100
	crop insurance coverage	crop insurance policies per square mile	2020	U.S. Department of Agriculture (USDA). (2020). State/County/Crop Summary of Business. https://www.rma.usda.gov/en/Information-Tools/Summary-of-Business/State-County-Crop-Summary-of-Business		Zero	Number of crop insurance policies / County area (square miles)
Housing/Infrastructural	sturdier housing types	% housing units not manufactured homes	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	100 - [Pct total housing units mobile home]
	temporary housing availability	% vacant units that are for rent	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct total housing units rental vacancy rate
	medical care capacity	hospital beds per 10,000 persons	2023	U.S. Department of Homeland Security (USDHS). (2023). Homeland infrastructure foundation-level data (HIFLD) database: Hospitals. https://hifld-geoplatform.opendata.arcgis.com/	Y	Zero	[Number of hospital beds / County population] * 10,000
	evacuation routes	major road egress points per 10,000 persons	2023	U.S. Geological Survey (USGS). (2023). National atlas. https://www.usgs.gov/programs/national-geospatial-program/national-map		Zero	[Number of road egress points / County population] * 10,000
	housing stock construction quality	% housing units built prior to 1970 or after 2000	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates		Null	Pct housing units built prior to 1970 or after 2000
	temporary shelter availability	hotels/motels per 10,000 persons	2020	U.S. Census Bureau. (2020). County business patterns. https://www.census.gov/programs-surveys/cbp/data/datasets.html		Zero	[Number of hotels/motels / County population] * 10,000
	school restoration potential	public schools per 10,000 persons	2020–2021	U.S. Department of Education (USDE) National Center for Education Statistics (NCES). 2020–2021. Education demographic and geographic estimates: School locations and geoassignments 2020–2021. https://nces.ed.gov/programs/edge/geographic/schoollocations		Zero	[Number of public schools / County population] * 10,000

Domain	Indicator	Measure	Year	Source	Alt Data Used	Handling Missing Data	Calculation
Housing/Infrastructural (cont.)	industrial re-supply potential	rail miles per square mile	2020	U.S. Census Bureau. (2020). Tiger/Line shapefiles. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2020.html#list-tab-790442341		Zero	Sum of rail miles / County area (square miles)
	high speed internet infrastructure	% population with access to broadband internet service	2016–2020	U.S. Census Bureau. 2016–2020 American Community Survey 5-Year Estimates	Y	Null	Pct population with access to broadband internet service
Environmental	local food suppliers	farms marketing products through Community Supported Agriculture (CSA) per 10,000 persons	2020	U.S. Department of Agriculture (USDA). (2020). Census of agriculture. https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Local_Food/index.php U.S. Department of Agriculture (USDA). (2023). Local food directories. https://www.usdalocalfoodportal.com/fe/fdirectory_csa/?source=fe&directory=csa&location=&x=&y=		Null	[Number of farms marketing through CSAs / County population] * 10,000
	natural flood buffers	% land in wetlands	2019	U.S. Geological Survey (USGS). (2019). National land cover dataset. https://www.usgs.gov/centers/eros/science/national-land-cover-database		Null	[Wetland area / County area] *100
		megawatt hours per energy consumer	2020	U.S. Energy Information Administration (USEIA). (2020). Electricity consumption. https://www.eia.gov/electricity/		Null	Net Generation (Megawatthours) / County population
	pervious surfaces	average percent perviousness	2019	U.S. Geological Survey (USGS). (2019). National land cover dataset. https://www.usgs.gov/centers/eros/science/national-land-cover-database		Null	100 − {[Impervious surfaces area / County area] *100}
	efficient water use	domestic per capita use self-supply (in gallons/person/day)	2015	U.S. Geological Survey (USGS). (2015). National water information system: water use. https://waterdata.usgs.gov/nwis/water_use	Y	Null	Domestic, self-supplied per capita use, in gallons/day [DO-WFrTo/DO-SSPop*1000]

Appendix C: CRSI and BRIC Scores

Table C1. CRSI scores for all coastal counties sorted by total resilience in descending order.

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
1	Dillingham Census Area, AK	0.00	0.26	0.42	0.18	0.06	9740.28
2	Benzie County, MI	0.00	0.58	0.57	0.17	0.30	838.38
3	Bethel Census Area, AK	0.00	0.59	0.25	0.33	0.29	330.06
4	Alcona County, MI	0.00	0.52	0.40	0.20	0.31	185.08
5	Alpena County, MI	0.00	0.60	0.44	0.15	0.32	180.59
6	Nome Census Area, AK	0.00	0.53	0.34	0.26	0.18	169.37
7	Copper River Census Area, AK	0.00	0.23	0.42	0.24	0.23	148.43
8	Hoonah-Angoon Census Area, AK	0.00	0.23	0.59	0.16	0.73	147.28
9	Ketchikan Gateway Borough, AK	0.00	0.24	0.54	0.11	0.71	137.41
10	Aleutians East Borough, AK	0.00	0.23	0.63	0.11	0.36	133.99
11	Aleutians West Census Area, AK	0.01	0.29	0.71	0.11	0.56	129.72
12	Kusilvak Census Area, AK	0.01	0.44	0.19	0.26	0.63	128.67
13	Lake and Peninsula Borough, AK	0.00	0.21	0.39	0.16	0.15	125.47
14	Cheboygan County, MI	0.00	0.58	0.39	0.17	0.21	112.78
15	Skagway Municipality, AK	0.01	0.51	0.66	0.15	0.20	112.75
16	Arenac County, MI	0.01	0.61	0.46	0.20	0.39	95.22
17	Oceana County, MI	0.01	0.62	0.40	0.20	0.27	94.83
18	Prince of Wales-Hyder Census Area, AK	0.00	0.24	0.33	0.22	0.49	86.11
19	Juneau City and Borough, AK	0.01	0.26	0.62	0.15	0.56	80.76
20	Wrangell City and Borough, AK	0.01	0.23	0.49	0.16	0.51	75.61
21	Matanuska-Susitna Borough, AK	0.00	0.23	0.49	0.30	0.15	73.46
22	Presque Isle County, MI	0.01	0.56	0.42	0.17	0.30	68.68
23	Sitka City and Borough, AK	0.01	0.26	0.61	0.10	0.54	68.03
24	Kenai Peninsula Borough, AK	0.01	0.26	0.46	0.26	0.39	59.11
25	North Slope Borough, AK	0.00	0.23	0.52	0.12	0.33	58.92
26	Northwest Arctic Borough, AK	0.01	0.25	0.34	0.25	0.31	56.45
27	Hawaii County, HI	0.03	0.65	0.18	0.18	0.80	51.30
28	Chugach Census Area, AK	0.02	0.24	0.64	0.28	0.54	49.77
29	Lake County, MN	0.03	0.60	0.68	0.13	0.54	48.00
30	Ontonagon County, MI	0.01	0.27	0.45	0.12	0.29	46.24
31	Keweenaw County, MI	0.03	0.58	0.56	0.19	0.52	46.22
32	Petersburg Borough, AK	0.02	0.25	0.69	0.15	0.56	36.22
33	Iron County, WI	0.02	0.76	0.48	0.13	0.26	35.87
34	Manistee County, MI	0.02	0.57	0.51	0.15	0.33	33.88
35	Yakutat City and Borough, AK	0.01	0.19	0.53	0.15	0.39	29.12
36	Haines Borough, AK	0.02	0.22	0.74	0.16	0.29	28.89
37	Cook County, MN	0.04	0.58	0.61	0.10	0.55	27.74

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
38	Mason County, MI	0.01	0.28	0.42	0.16	0.32	26.39
39	Gogebic County, MI	0.01	0.19	0.41	0.09	0.40	25.79
40	Baraga County, MI	0.02	0.62	0.43	0.17	0.21	25.66
41	Bristol Bay Borough, AK	0.01	0.21	0.72	0.10	0.06	24.42
42	Kenosha County, WI	0.04	0.89	0.24	0.19	0.45	23.92
43	Leelanau County, MI	0.03	0.33	0.65	0.18	0.36	23.71
44	Grand Traverse County, MI	0.02	0.55	0.56	0.17	0.07	23.70
45	Iosco County, MI	0.02	0.58	0.30	0.17	0.31	20.71
46	Huron County, MI	0.03	0.53	0.49	0.15	0.31	18.59
47	St. Louis County, MN	0.05	0.61	0.38	0.30	0.17	16.95
48	Dukes County, MA	0.05	0.60	0.59	0.17	0.21	16.94
49	Antrim County, MI	0.02	0.32	0.53	0.19	0.11	16.58
50	St. Clair County, MI	0.03	0.56	0.45	0.16	0.25	16.31
51	Tuscola County, MI	0.03	0.32	0.45	0.19	0.30	16.30
52	Kauai County, HI	0.09	0.59	0.32	0.15	0.73	14.36
53	Oswego County, NY	0.05	0.53	0.52	0.18	0.27	13.16
54	Emmet County, MI	0.03	0.53	0.34	0.19	0.17	11.34
55	Anchorage Municipality, AK	0.03	0.21	0.53	0.25	0.22	11.03
56	Bay County, MI	0.03	0.28	0.44	0.16	0.35	10.32
57	Allegan County, MI	0.09	0.56	0.55	0.20	0.31	10.23
58	Erie County, OH	0.04	0.27	0.47	0.17	0.31	9.61
59	Erie County, PA	0.07	0.62	0.28	0.24	0.29	9.41
60	Ashland County, WI	0.03	0.20	0.42	0.13	0.51	8.90
61	Cayuga County, NY	0.08	0.62	0.55	0.18	0.18	8.77
62	Mathews County, VA	0.23	0.64	0.75	0.17	0.63	8.68
63	Marinette County, WI	0.14	0.83	0.46	0.21	0.29	8.28
64	Van Buren County, MI	0.07	0.56	0.31	0.16	0.39	8.07
65	Los Angeles County, CA	0.32	0.61	0.26	1.00	0.01	8.01
66	Sandusky County, OH	0.03	0.21	0.48	0.19	0.25	7.91
67	Niagara County, NY	0.13	0.53	0.57	0.17	0.44	7.89
68	Honolulu County, HI	0.20	0.62	0.30	0.21	0.75	7.57
69	Wakulla County, FL	0.15	0.59	0.35	0.18	0.55	6.79
70	Charlevoix County, MI	0.04	0.24	0.58	0.17	0.18	6.76
71	Kodiak Island Borough, AK	0.02	0.19	0.60	0.04	0.24	6.47
72	Porter County, IN	0.06	0.27	0.49	0.18	0.32	6.11
73	Monroe County, MI	0.07	0.35	0.48	0.15	0.32	6.00
74	Harris County, TX	0.12	0.29	0.12	0.65	0.17	5.96
75	Schoolcraft County, MI	0.21	0.58	0.53	0.11	0.59	5.66
76	Victoria County, TX	0.07	0.52	0.20	0.20	0.32	5.51
77	Middlesex County, VA	0.22	0.55	0.66	0.18	0.38	5.28
78	Delta County, MI	0.28	0.89	0.42	0.17	0.48	5.27

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
79	Ottawa County, MI	0.06	0.25	0.42	0.20	0.30	4.98
80	Bayfield County, WI	0.03	0.35	0.50	0.04	0.22	4.93
81	Ottawa County, OH	0.16	0.59	0.38	0.16	0.42	4.93
82	Houghton County, MI	0.05	0.26	0.45	0.17	0.23	4.92
83	Ozaukee County, WI	0.17	0.33	0.71	0.17	0.51	4.91
84	Mackinac County, MI	0.16	0.59	0.37	0.18	0.39	4.91
85	Arlington County, VA	0.37	0.66	0.77	0.16	0.49	4.77
86	Racine County, WI	0.10	0.24	0.48	0.19	0.48	4.74
87	Monroe County, FL	0.36	0.61	0.29	0.24	0.82	4.72
88	Erie County, NY	0.16	0.54	0.34	0.30	0.24	4.67
89	King and Queen County, VA	0.28	0.54	0.74	0.17	0.41	4.56
90	Dare County, NC	0.23	0.29	0.49	0.20	1.00	4.55
91	Carteret County, NC	0.28	0.61	0.38	0.18	0.64	4.54
92	Orleans County, NY	0.05	0.52	0.26	0.19	0.19	4.41
93	Berrien County, MI	0.15	0.58	0.29	0.20	0.38	4.32
94	Chesapeake City, VA	0.26	0.62	0.50	0.16	0.46	4.32
95	Brazoria County, TX	0.21	0.56	0.29	0.25	0.44	4.31
96	Wayne County, NY	0.07	0.26	0.38	0.18	0.31	4.30
97	Snohomish County, WA	0.18	0.71	0.35	0.18	0.33	4.24
98	Gloucester County, VA	0.31	0.64	0.54	0.18	0.47	4.19
99	Menominee County, MI	0.17	0.68	0.46	0.16	0.26	4.15
100	Richmond County, VA	0.27	0.61	0.58	0.18	0.37	4.13
101	Manitowoc County, WI	0.40	0.82	0.62	0.19	0.37	4.06
102	Kent County, MD	0.29	0.63	0.45	0.15	0.56	4.05
103	LaPorte County, IN	0.08	0.26	0.39	0.16	0.39	4.04
104	Bryan County, GA	0.10	0.23	0.50	0.18	0.44	4.03
105	Surry County, VA	0.32	0.65	0.62	0.18	0.37	4.01
106	Prince George County, VA	0.27	0.65	0.69	0.16	0.25	3.94
107	Prince William County, VA	0.23	0.67	0.52	0.16	0.29	3.90
108	Sanilac County, MI	0.03	0.33	0.41	0.00	0.36	3.81
109	King County, WA	0.23	0.43	0.34	0.34	0.37	3.78
110	Cape May County, NJ	0.29	0.53	0.53	0.19	0.48	3.77
111	Jefferson County, NY	0.05	0.30	0.28	0.18	0.25	3.76
112	Caroline County, VA	0.31	0.63	0.62	0.18	0.33	3.72
113	Nantucket County, MA	0.26	0.62	0.76	0.11	0.24	3.71
114	Camden County, NC	0.32	0.58	0.46	0.17	0.56	3.70
115	Charles City County, VA	0.24	0.53	0.61	0.17	0.31	3.63
116	Cuyahoga County, OH	0.13	0.57	0.17	0.25	0.30	3.62
117	Chautauqua County, NY	0.11	0.30	0.42	0.20	0.30	3.60
118	King George County, VA	0.36	0.53	0.82	0.15	0.38	3.60
119	Whatcom County, WA	0.12	0.36	0.30	0.19	0.40	3.56

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
120	Pamlico County, NC	0.30	0.63	0.36	0.19	0.50	3.54
121	Pasquotank County, NC	0.30	0.59	0.31	0.13	0.68	3.53
122	King William County, VA	0.31	0.49	0.79	0.15	0.34	3.49
123	Cameron Parish, LA	0.28	0.62	0.49	0.20	0.32	3.47
124	Cecil County, MD	0.29	0.56	0.49	0.17	0.44	3.41
125	York County, VA	0.35	0.57	0.57	0.15	0.49	3.29
126	Westmoreland County, VA	0.28	0.60	0.44	0.18	0.41	3.29
127	Lake County, OH	0.11	0.26	0.58	0.14	0.29	3.28
128	San Diego County, CA	0.31	0.59	0.25	0.47	0.11	3.16
129	Poquoson City, VA	0.32	0.38	1.00	0.08	0.42	3.15
130	Hyde County, NC	0.32	0.50	0.32	0.19	0.63	3.12
131	Fairfax County, VA	0.38	0.59	0.65	0.18	0.36	3.08
132	Lorain County, OH	0.12	0.54	0.27	0.16	0.32	3.05
133	New Kent County, VA	0.24	0.28	0.90	0.16	0.35	2.96
134	Suffolk County, NY	0.47	0.60	0.46	0.32	0.38	2.95
135	Harford County, MD	0.35	0.53	0.57	0.19	0.41	2.93
136	Calhoun County, TX	0.11	0.46	0.32	0.13	0.33	2.93
137	James City County, VA	0.28	0.52	0.54	0.15	0.37	2.93
138	Douglas County, WI	0.04	0.20	0.39	0.15	0.21	2.93
139	Brevard County, FL	0.26	0.53	0.20	0.22	0.51	2.88
140	Livingston Parish, LA	0.22	0.63	0.33	0.18	0.33	2.81
141	Sheboygan County, WI	0.30	0.35	0.60	0.19	0.49	2.76
142	Queen Anne's County, MD	0.29	0.35	0.61	0.18	0.48	2.75
143	Mason County, WA	0.13	0.96	0.38	0.15	0.15	2.74
144	Kitsap County, WA	0.18	0.86	0.32	0.17	0.23	2.74
145	Chippewa County, MI	0.12	0.27	0.34	0.19	0.37	2.73
146	Taylor County, FL	0.13	0.53	0.18	0.19	0.35	2.72
147	Howard County, MD	0.38	0.58	0.62	0.16	0.34	2.69
148	Talbot County, MD	0.28	0.50	0.46	0.15	0.43	2.69
149	Aransas County, TX	0.18	0.62	0.26	0.15	0.38	2.69
150	Jasper County, SC	0.19	0.62	0.38	0.21	0.19	2.64
151	Accomack County, VA	0.31	0.53	0.16	0.21	0.58	2.61
152	Stafford County, VA	0.36	0.65	0.59	0.16	0.27	2.59
153	Alger County, MI	0.23	0.39	0.51	0.14	0.42	2.55
154	Refugio County, TX	0.04	0.58	0.24	0.19	0.14	2.48
155	Oconto County, WI	0.25	0.31	0.62	0.20	0.36	2.47
156	Dorchester County, MD	0.39	0.55	0.32	0.15	0.63	2.47
157	Newport County, RI	0.25	0.57	0.55	0.16	0.20	2.46
158	Skagit County, WA	0.12	0.45	0.27	0.15	0.33	2.46
159	Hanover County, VA	0.35	0.51	0.67	0.16	0.28	2.46
160	Currituck County, NC	0.24	0.24	0.45	0.18	0.65	2.44

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
161	Liberty County, GA	0.21	0.55	0.28	0.16	0.39	2.44
162	Lancaster County, VA	0.28	0.33	0.55	0.17	0.50	2.42
163	Liberty County, FL	0.22	0.28	0.43	0.21	0.47	2.42
164	Clallam County, WA	0.12	0.27	0.37	0.15	0.37	2.40
165	Macomb County, MI	0.13	0.32	0.46	0.16	0.24	2.38
166	Middlesex County, CT	0.26	0.56	0.40	0.17	0.32	2.37
167	Essex County, VA	0.29	0.60	0.44	0.17	0.28	2.36
168	Martin County, FL	0.19	0.63	0.25	0.18	0.30	2.33
169	Douglas County, OR	0.30	0.55	0.38	0.25	0.26	2.32
170	Chambers County, TX	0.18	0.28	0.50	0.20	0.31	2.31
171	New London County, CT	0.32	0.55	0.44	0.23	0.25	2.31
172	Lane County, OR	0.28	0.49	0.21	0.35	0.25	2.30
173	Caroline County, MD	0.32	0.58	0.44	0.15	0.38	2.30
174	Barnstable County, MA	0.25	0.49	0.39	0.22	0.25	2.29
175	Cumberland County, ME	0.37	0.60	0.42	0.26	0.25	2.28
176	Henrico County, VA	0.33	0.66	0.49	0.16	0.27	2.28
177	Tyrrell County, NC	0.29	0.32	0.30	0.21	0.63	2.24
178	Jefferson County, FL	0.09	0.26	0.22	0.24	0.25	2.22
179	San Juan County, WA	0.10	0.15	0.53	0.15	0.38	2.22
180	Chowan County, NC	0.34	0.64	0.40	0.16	0.37	2.22
181	Washington County, RI	0.27	0.45	0.44	0.16	0.38	2.21
182	St. Tammany Parish, LA	0.30	0.60	0.34	0.18	0.36	2.20
183	Charleston County, SC	0.44	0.46	0.43	0.20	0.55	2.19
184	Muskegon County, MI	0.10	0.26	0.37	0.16	0.28	2.17
185	Jones County, NC	0.45	0.59	0.25	0.22	0.52	2.16
186	Camden County, GA	0.22	0.57	0.31	0.19	0.29	2.15
187	Knox County, ME	0.29	0.62	0.34	0.16	0.35	2.13
188	Virginia Beach City, VA	0.28	0.27	0.49	0.16	0.62	2.12
189	Kalawao County, HI	0.19	0.31	0.99	0.09		2.06
190	Charles County, MD	0.35	0.54	0.47	0.17	0.33	2.05
191	Lake County, IL	0.12	0.26	0.36	0.21	0.25	2.05
192	Putnam County, NY	0.35	0.43	0.72	0.19	0.18	2.04
193	Luce County, MI	0.22	0.36	0.51	0.12	0.34	2.03
194	Monroe County, NY	0.17	0.28	0.30	0.25	0.31	2.03
195	Ascension Parish, LA	0.25	0.61	0.36	0.17	0.25	2.03
196	Chatham County, GA	0.23	0.41	0.17	0.18	0.52	2.02
197	Bristol County, RI	0.22	0.50	0.58	0.14	0.13	1.96
198	Worcester County, MD	0.47	0.52	0.40	0.16	0.54	1.96
199	Washington County, NC	0.36	0.54	0.20	0.22	0.47	1.94
200	Lake County, IN	0.15	0.62	0.32	0.16	0.22	1.94
201	Cook County, IL	0.18	0.18	0.20	0.47	0.24	1.93

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
202	Assumption Parish, LA	0.25	0.68	0.30	0.22	0.20	1.92
203	Orange County, TX	0.27	0.56	0.27	0.17	0.38	1.92
204	Salem County, NJ	0.30	0.57	0.22	0.19	0.40	1.89
205	Northampton County, VA	0.29	0.31	0.44	0.19	0.46	1.88
206	Alexandria City, VA	0.35	0.61	0.55	0.17	0.17	1.88
207	Galveston County, TX	0.20	0.59	0.23	0.18	0.30	1.87
208	Atlantic County, NJ	0.31	0.53	0.19	0.22	0.41	1.86
209	Franklin County, FL	0.26	0.26	0.36	0.14	0.63	1.83
210	Volusia County, FL	0.36	0.64	0.15	0.22	0.43	1.81
211	Gates County, NC	0.40	0.55	0.29	0.20	0.42	1.81
212	Craven County, NC	0.42	0.54	0.28	0.15	0.54	1.79
213	Jefferson County, WA	0.11	0.15	0.40	0.15	0.42	1.79
214	Milwaukee County, WI	0.20	0.30	0.35	0.25	0.25	1.78
215	Middlesex County, NJ	0.34	0.50	0.30	0.24	0.32	1.75
216	Plaquemines Parish, LA	0.21	0.23	0.44	0.20	0.38	1.74
217	Door County, WI	0.33	0.27	0.57	0.22	0.40	1.73
218	Somerset County, NJ	0.28	0.33	0.61	0.18	0.23	1.72
219	Berkeley County, SC	0.48	0.49	0.37	0.20	0.49	1.71
220	Levy County, FL	0.35	0.51	0.29	0.24	0.32	1.71
221	Wayne County, MI	0.12	0.53	0.09	0.22	0.29	1.70
222	Calvert County, MD	0.32	0.27	0.60	0.17	0.43	1.70
223	Hancock County, ME	0.26	0.53	0.34	0.20	0.23	1.67
224	Gulf County, FL	0.24	0.26	0.52	0.09	0.48	1.67
225	Pender County, NC	0.51	0.68	0.31	0.19	0.40	1.67
226	Baltimore County, MD	0.36	0.64	0.29	0.21	0.30	1.65
227	Spotsylvania County, VA	0.25	0.63	0.49	0.14	0.15	1.65
228	Hampton County, SC	0.30	0.49	0.38	0.19	0.28	1.64
229	Newport News City, VA	0.40	1.00	0.33	0.15	0.28	1.62
230	Burlington County, NJ	0.45	0.58	0.33	0.23	0.32	1.61
231	Palm Beach County, FL	0.34	0.59	0.14	0.25	0.37	1.60
232	Wicomico County, MD	0.34	0.48	0.32	0.16	0.41	1.58
233	Hopewell City, VA	0.34	0.75	0.21	0.10	0.49	1.58
234	Hillsborough County, FL	0.17	0.26	0.20	0.30	0.26	1.58
235	McIntosh County, GA	0.25	0.24	0.33	0.20	0.50	1.55
236	Richmond County, NY	0.51	0.63	0.38	0.18	0.35	1.49
237	Ocean County, NJ	0.44	0.50	0.33	0.23	0.33	1.48
238	Sarasota County, FL	0.19	0.28	0.30	0.17	0.37	1.45
239	Northumberland County, VA	0.43	0.33	0.61	0.18	0.37	1.43
240	New York County, NY	0.56	0.49	0.30	0.33	0.29	1.41
241	Isle of Wight County, VA	0.36	0.46	0.44	0.16	0.29	1.41
242	Cumberland County, NJ	0.28	0.58	0.13	0.22	0.35	1.41

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
243	Gloucester County, NJ	0.35	0.25	0.61	0.20	0.35	1.39
244	Jackson County, MS	0.27	0.34	0.16	0.13	0.58	1.37
245	York County, ME	0.40	0.53	0.39	0.22	0.22	1.37
246	San Mateo County, CA	0.51	0.50	0.42	0.25	0.26	1.34
247	Waldo County, ME	0.31	0.59	0.30	0.19	0.25	1.32
248	Indian River County, FL	0.08	0.28	0.16	0.17	0.31	1.32
249	Bertie County, NC	0.46	0.50	0.15	0.23	0.47	1.32
250	Santa Cruz County, CA	0.25	0.58	0.35	0.20	0.15	1.31
251	St. Mary's County, MD	0.36	0.32	0.55	0.18	0.29	1.30
252	Marquette County, MI	0.19	0.26	0.30	0.20	0.30	1.29
253	Humboldt County, CA	0.23	0.27	0.16	0.30	0.30	1.29
254	Okaloosa County, FL	0.27	0.52	0.27	0.19	0.27	1.29
255	Pitt County, NC	0.45	0.55	0.28	0.19	0.37	1.28
256	Calcasieu Parish, LA	0.29	0.63	0.21	0.22	0.24	1.27
257	Santa Clara County, CA	0.46	0.47	0.39	0.34	0.08	1.27
258	New Hanover County, NC	0.31	0.48	0.27	0.15	0.38	1.25
259	Dutchess County, NY	0.37	0.56	0.37	0.23	0.16	1.24
260	Island County, WA	0.15	0.27	0.46	0.12	0.22	1.23
261	Santa Barbara County, CA	0.31	0.28	0.29	0.33	0.23	1.23
262	Sussex County, DE	0.32	0.24	0.35	0.24	0.40	1.22
263	Bristol County, MA	0.31	0.47	0.30	0.23	0.20	1.21
264	Orange County, CA	0.56	0.55	0.30	0.33	0.18	1.21
265	Ashtabula County, OH	0.07	0.24	0.18	0.17	0.27	1.20
266	Ventura County, CA	0.50	0.52	0.34	0.28	0.20	1.19
267	Plymouth County, MA	0.25	0.23	0.41	0.23	0.26	1.18
268	Curry County, OR	0.26	0.83	0.30	0.15	0.21	1.17
269	Jackson County, TX	0.13	0.45	0.29	0.14	0.22	1.17
270	Wayne County, GA	0.31	0.66	0.40	0.17	0.14	1.16
271	Collier County, FL	0.33	0.26	0.17	0.16	0.64	1.14
272	Miami-Dade County, FL	0.40	0.27	0.12	0.30	0.54	1.13
273	Orange County, NY	0.39	0.62	0.31	0.25	0.14	1.12
274	Maui County, HI	0.10	0.14	0.29	0.16	0.33	1.11
275	Brunswick County, NC	0.56	0.63	0.19	0.21	0.39	1.10
276	Putnam County, FL	0.26	0.62	0.07	0.23	0.30	1.10
277	Perquimans County, NC	0.34	0.34	0.34	0.15	0.40	1.10
278	Thurston County, WA	0.11	0.22	0.30	0.18	0.21	1.10
279	Hampton City, VA	0.38	0.28	0.33	0.13	0.56	1.10
280	Charlotte County, FL	0.23	0.30	0.15	0.18	0.43	1.08
281	Lincoln County, ME	0.30	0.62	0.33	0.18	0.18	1.08
282	Monmouth County, NJ	0.36	0.22	0.40	0.24	0.39	1.04
283	Santa Rosa County, FL	0.33	0.30	0.28	0.19	0.40	1.03

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
284	Westchester County, NY	0.54	0.51	0.35	0.23	0.25	1.03
285	Chesterfield County, VA	0.40	0.27	0.49	0.18	0.35	1.02
286	Somerset County, MD	0.25	0.22	0.28	0.13	0.51	1.02
287	Colleton County, SC	0.44	0.50	0.35	0.23	0.20	1.01
288	San Luis Obispo County, CA	0.28	0.58	0.37	0.25	0.02	1.01
289	St. Johns County, FL	0.20	0.31	0.34	0.17	0.23	1.00
290	Charlton County, GA	0.28	0.24	0.17	0.23	0.45	1.00
291	Brown County, WI	0.43	0.30	0.39	0.24	0.31	1.00
292	Pasco County, FL	0.11	0.68	0.14	0.21	0.19	0.99
293	Marin County, CA	0.36	0.21	0.40	0.20	0.44	0.99
294	San Francisco County, CA	0.73	0.63	0.37	0.24	0.23	0.99
295	Manatee County, FL	0.06	0.50	0.16	0.18	0.21	0.96
296	Nueces County, TX	0.36	0.57	0.18	0.25	0.21	0.95
297	Hancock County, MS	0.25	0.33	0.14	0.18	0.41	0.95
298	Kent County, RI	0.29	0.32	0.42	0.15	0.26	0.94
299	St. James Parish, LA	0.21	0.25	0.30	0.19	0.26	0.90
300	Harrison County, MS	0.31	0.29	0.13	0.15	0.54	0.90
301	Fairfield County, CT	0.64	0.58	0.27	0.27	0.22	0.90
302	Contra Costa County, CA	0.27	0.26	0.31	0.28	0.16	0.88
303	Tangipahoa Parish, LA	0.23	0.56	0.11	0.19	0.31	0.86
304	St. Bernard Parish, LA	0.22	0.57	0.03	0.16	0.43	0.84
305	Baldwin County, AL	0.32	0.22	0.27	0.23	0.37	0.84
306	Hertford County, NC	0.47	0.59	0.23	0.14	0.39	0.83
307	Strafford County, NH	0.44	0.64	0.32	0.20	0.17	0.81
308	Queens County, NY	0.60	0.50	0.20	0.25	0.31	0.79
309	Onslow County, NC	0.44	0.28	0.30	0.15	0.49	0.79
310	Pacific County, WA	0.12	0.44	0.37	0.11	0.17	0.78
311	San Patricio County, TX	0.15	0.82	0.32	0.18	0.07	0.77
312	Jefferson County, TX	0.28	0.90	0.12	0.17	0.31	0.77
313	Sagadahoc County, ME	0.26	0.33	0.41	0.17	0.15	0.77
314	Monterey County, CA	0.25	0.21	0.25	0.32	0.15	0.74
315	Georgetown County, SC	0.64	0.54	0.26	0.19	0.34	0.74
316	Vermilion Parish, LA	0.29	0.55	0.15	0.13	0.39	0.74
317	Willacy County, TX	0.49	0.59	0.23	0.12	0.39	0.74
318	Alameda County, CA	0.26	0.24	0.34	0.31	0.04	0.73
319	Kent County, DE	0.44	0.27	0.24	0.21	0.41	0.72
320	Grays Harbor County, WA	0.16	0.18	0.32	0.14	0.29	0.72
321	Anne Arundel County, MD	0.43	0.25	0.37	0.20	0.33	0.71
322	Nassau County, NY	0.52	0.25	0.47	0.23	0.28	0.70
323	Horry County, SC	0.71	0.56	0.33	0.19	0.28	0.70
324	Clay County, FL	0.26	0.58	0.30	0.17	0.16	0.70

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
325	Dorchester County, SC	0.31	0.62	0.37	0.16	0.12	0.69
326	Beaufort County, NC	0.42	0.24	0.24	0.17	0.49	0.68
327	Cameron County, TX	0.52	0.26	0.23	0.23	0.45	0.68
328	Portsmouth City, VA	0.44	0.85	0.31	0.14	0.20	0.66
329	Norfolk City, VA	0.44	0.21	0.44	0.16	0.36	0.65
330	Brantley County, GA	0.27	0.20	0.36	0.23	0.17	0.64
331	Ulster County, NY	0.31	0.36	0.33	0.24	0.09	0.62
332	Escambia County, FL	0.30	0.26	0.20	0.18	0.35	0.62
333	Lee County, FL	0.21	0.24	0.16	0.21	0.28	0.60
334	New Castle County, DE	0.76	0.27	0.40	0.22	0.39	0.59
335	Beaufort County, SC	0.40	0.24	0.44	0.13	0.31	0.58
336	District of Columbia, DC	0.76	0.26	0.51	0.23	0.31	0.58
337	Clatsop County, OR	0.15	0.16	0.46	0.12	0.17	0.57
338	Lafourche Parish, LA	0.22	0.28	0.19	0.20	0.25	0.57
339	Williamsburg City, VA	0.46	0.29	0.45	0.14	0.27	0.57
340	Camden County, NJ	0.44	0.30	0.24	0.21	0.30	0.56
341	Glynn County, GA	0.28	0.29	0.16	0.13	0.43	0.56
342	Sonoma County, CA	0.46	0.29	0.33	0.25	0.18	0.56
343	Pierce County, WA	0.18	0.11	0.27	0.27	0.21	0.56
344	Flagler County, FL	0.53	0.24	0.33	0.17	0.39	0.53
345	Dixie County, FL	0.57	0.22	0.29	0.25	0.37	0.53
346	Delaware County, PA	0.34	0.57	0.30	0.18	0.14	0.52
347	Napa County, CA	0.50	0.25	0.37	0.19	0.27	0.49
348	Hudson County, NJ	0.61	0.57	0.19	0.20	0.27	0.49
349	Philadelphia County, PA	0.49	0.55	0.09	0.27	0.21	0.49
350	Walton County, FL	0.35	0.21	0.29	0.20	0.27	0.48
351	Citrus County, FL	0.28	0.26	0.14	0.21	0.30	0.48
352	Nassau County, FL	0.18	0.10	0.29	0.18	0.32	0.48
353	Middlesex County, MA	1.00	0.32	0.42	0.31	0.19	0.48
354	St. Martin Parish, LA	0.23	0.20	0.30	0.17	0.23	0.48
355	Prince George's County, MD	0.40	0.31	0.24	0.20	0.25	0.47
356	Matagorda County, TX	0.32	0.22	0.26	0.16	0.34	0.47
357	Norfolk County, MA	0.74	0.31	0.43	0.23	0.19	0.47
358	Suffolk County, MA	0.44	0.34	0.24	0.24	0.18	0.46
359	Providence County, RI	0.44	0.53	0.20	0.22	0.19	0.46
360	Duval County, FL	0.78	0.27	0.23	0.26	0.38	0.45
361	Kings County, NY	0.61	0.58	0.13	0.20	0.31	0.42
362	Rockingham County, NH	0.50	0.22	0.38	0.22	0.18	0.40
363	Rockland County, NY	0.51	0.23	0.35	0.18	0.28	0.39
364	Essex County, MA	0.61	0.23	0.31	0.24	0.24	0.36
365	Solano County, CA	0.41	0.25	0.27	0.23	0.16	0.35

	County	Risk	Governance	Society	Built Environment	Natural Environment	Total Resilience
366	St. Charles Parish, LA	0.26	0.17	0.28	0.20	0.20	0.35
367	St. John the Baptist Parish, LA	0.25	0.21	0.21	0.18	0.25	0.33
368	Bay County, FL	0.40	0.20	0.23	0.16	0.35	0.33
369	New Haven County, CT	0.59	0.23	0.22	0.26	0.22	0.31
370	Suffolk City, VA	0.55	0.20	0.39	0.16	0.27	0.31
371	Essex County, NJ	0.56	0.33	0.14	0.20	0.30	0.28
372	Wahkiakum County, WA	0.11	0.18	0.49	0.06	0.14	0.28
373	Bergen County, NJ	0.61	0.23	0.34	0.21	0.18	0.28
374	Mendocino County, CA	0.44	0.23	0.16	0.28	0.15	0.25
375	Broward County, FL	0.75	0.25	0.15	0.22	0.34	0.24
376	Orleans Parish, LA	0.25	0.18	0.11	0.20	0.28	0.24
377	St. Mary Parish, LA	0.23	0.47	0.08	0.19	0.26	0.23
378	Mobile County, AL	0.46	0.22	0.17	0.17	0.32	0.22
379	Kenedy County, TX	0.24	0.17	0.23	0.26	0.06	0.20
380	Del Norte County, CA	0.46	0.25	0.16	0.10	0.42	0.19
381	Jefferson Davis Parish, LA	0.30	0.12	0.35	0.16	0.17	0.18
382	Lucas County, OH	0.07	0.20	0.17	0.13	0.26	0.16
383	Jefferson Parish, LA	0.26	0.70	0.16	0.18	0.19	0.10
384	Union County, NJ	0.58	0.28	0.24	0.20	0.11	0.07
385	Terrebonne Parish, LA	0.24	0.15	0.14	0.17	0.23	0.06
386	Bronx County, NY	0.55	0.34	0.00	0.23	0.25	0.03
387	Pinellas County, FL	0.57	0.00	0.19	0.20	0.13	0.00
388	Kewaunee County, WI	0.37	0.00	0.79	0.16	0.40	0.00
389	Baltimore City, MD	0.49	0.22	0.18	0.17	0.16	-0.02
390	Kleberg County, TX	0.19	0.46	0.23	0.14	0.17	-0.11
391	Washington County, ME	0.24	0.54	0.14	0.16	0.21	-0.12
392	St. Lucie County, FL	0.19	0.28	0.12	0.14	0.18	-0.42
393	Iberia Parish, LA	0.23	0.62	0.14	0.12	0.23	-0.48
394	Hernando County, FL	0.21	0.47	0.12	0.20	0.09	-0.61
395	Tillamook County, OR	0.20	0.55	0.27	0.07	0.12	-1.29
396	Coos County, OR	0.25	0.64	0.26	0.13	0.00	-1.37
397	Lincoln County, OR	0.23	0.56	0.14	0.09	0.11	-1.82

Table C2. BRIC scores for all coastal counties sorted by total resilience in descending order.

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
1	St. James Parish, LA	0.53	0.56	0.67	0.40	0.26	0.68	3.10
2	Cameron Parish, LA	0.54	0.44	0.61	0.49	0.29	0.65	3.03
3	Brown County, WI	0.58	0.56	0.55	0.41	0.33	0.58	3.01
4	Cumberland County, ME	0.60	0.57	0.52	0.39	0.33	0.60	3.00
5	Plymouth County, MA	0.58	0.54	0.53	0.42	0.31	0.60	2.98
6	St. Louis County, MN	0.56	0.53	0.46	0.37	0.35	0.69	2.97
7	Dare County, NC	0.51	0.56	0.38	0.48	0.36	0.68	2.97
8	Ozaukee County, WI	0.61	0.52	0.52	0.39	0.31	0.61	2.96
9	Lake County, OH	0.54	0.57	0.57	0.42	0.31	0.56	2.95
10	Sheboygan County, WI	0.59	0.56	0.48	0.39	0.32	0.62	2.94
11	Cook County, MN	0.53	0.43	0.55	0.43	0.37	0.63	2.94
12	Lake County, MN	0.50	0.51	0.54	0.40	0.30	0.69	2.94
13	St. Charles Parish, LA	0.56	0.49	0.37	0.54	0.27	0.69	2.93
14	Middlesex County, CT	0.56	0.53	0.52	0.41	0.32	0.59	2.93
15	Kent County, RI	0.58	0.55	0.53	0.40	0.31	0.54	2.92
16	Lucas County, OH	0.55	0.55	0.50	0.40	0.38	0.54	2.92
17	Niagara County, NY	0.54	0.53	0.55	0.38	0.32	0.60	2.92
18	Hanover County, VA	0.58	0.59	0.48	0.41	0.28	0.58	2.91
19	Milwaukee County, WI	0.56	0.54	0.49	0.39	0.36	0.56	2.91
20	St. John the Baptist Parish, LA	0.57	0.53	0.38	0.53	0.26	0.64	2.91
21	Manitowoc County, WI	0.56	0.53	0.49	0.41	0.30	0.61	2.90
22	Gloucester County, NJ	0.57	0.58	0.45	0.42	0.31	0.57	2.90
23	Monroe County, NY	0.55	0.56	0.50	0.38	0.33	0.58	2.90
24	Burlington County, NJ	0.58	0.57	0.39	0.43	0.30	0.61	2.89
25	Chesapeake City, VA	0.58	0.59	0.38	0.40	0.29	0.65	2.89
26	Charleston County, SC	0.57	0.52	0.41	0.41	0.32	0.65	2.88
27	Berrien County, MI	0.52	0.54	0.49	0.45	0.29	0.59	2.88
28	Cape May County, NJ	0.51	0.52	0.35	0.45	0.39	0.66	2.88
29	Ulster County, NY	0.56	0.53	0.51	0.39	0.30	0.59	2.87
30	Marquette County, MI	0.55	0.51	0.45	0.36	0.34	0.65	2.87
31	San Luis Obispo County, CA	0.58	0.48	0.37	0.39	0.28	0.76	2.87
32	Erie County, NY	0.56	0.56	0.47	0.37	0.35	0.57	2.87
33	St. Tammany Parish, LA	0.54	0.52	0.49	0.41	0.36	0.54	2.87
34	Leelanau County, MI	0.49	0.55	0.55	0.36	0.29	0.62	2.86
35	Plaquemines Parish, LA	0.52	0.47	0.45	0.52	0.22	0.68	2.86
36	Pitt County, NC	0.55	0.54	0.39	0.47	0.30	0.61	2.86
37	Chatham County, GA	0.53	0.51	0.39	0.39	0.36	0.66	2.86
38	Alpena County, MI	0.51	0.52	0.48	0.37	0.29	0.69	2.85
39	Napa County, CA	0.64	0.51	0.41	0.41	0.31	0.57	2.85
40	Jefferson County, TX	0.49	0.53	0.48	0.43	0.32	0.62	2.85

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
41	Queen Anne's County, MD	0.56	0.54	0.43	0.44	0.26	0.61	2.84
42	Racine County, WI	0.56	0.54	0.44	0.40	0.32	0.58	2.84
43	Kewaunee County, WI	0.55	0.50	0.51	0.40	0.26	0.62	2.84
44	Spotsylvania County, VA	0.58	0.55	0.47	0.40	0.26	0.57	2.84
45	Sandusky County, OH	0.53	0.54	0.46	0.44	0.30	0.57	2.84
46	Dorchester County, MD	0.53	0.46	0.44	0.42	0.30	0.68	2.83
47	Anne Arundel County, MD	0.58	0.57	0.44	0.39	0.29	0.56	2.83
48	Jefferson Parish, LA	0.54	0.52	0.41	0.41	0.31	0.64	2.83
49	New Castle County, DE	0.57	0.58	0.36	0.41	0.35	0.56	2.83
50	Putnam County, NY	0.59	0.52	0.53	0.41	0.31	0.47	2.83
51	St. Mary Parish, LA	0.53	0.50	0.38	0.43	0.27	0.73	2.83
52	Mobile County, AL	0.54	0.53	0.48	0.38	0.29	0.61	2.83
53	Ottawa County, OH	0.50	0.50	0.50	0.47	0.26	0.59	2.83
54	Nueces County, TX	0.51	0.49	0.48	0.45	0.34	0.55	2.83
55	New London County, CT	0.55	0.48	0.44	0.45	0.31	0.60	2.82
56	Worcester County, MD	0.50	0.53	0.45	0.43	0.26	0.66	2.82
57	Charles County, MD	0.58	0.61	0.37	0.40	0.26	0.59	2.82
58	Rockland County, NY	0.58	0.57	0.40	0.42	0.32	0.53	2.82
59	Monmouth County, NJ	0.58	0.52	0.43	0.40	0.33	0.56	2.82
60	Lorain County, OH	0.53	0.54	0.46	0.39	0.32	0.57	2.82
61	New Kent County, VA	0.56	0.53	0.38	0.44	0.31	0.60	2.82
62	Bay County, MI	0.53	0.55	0.38	0.43	0.33	0.60	2.82
63	Wicomico County, MD	0.56	0.48	0.44	0.41	0.30	0.63	2.82
64	Oconto County, WI	0.54	0.51	0.48	0.38	0.25	0.67	2.82
65	Brazoria County, TX	0.54	0.53	0.46	0.41	0.28	0.61	2.81
66	Erie County, PA	0.55	0.57	0.40	0.38	0.33	0.59	2.81
67	Orleans Parish, LA	0.55	0.46	0.43	0.39	0.36	0.62	2.81
68	Emmet County, MI	0.53	0.50	0.49	0.35	0.31	0.63	2.81
69	Schoolcraft County, MI	0.49	0.43	0.46	0.40	0.31	0.72	2.81
70	Muskegon County, MI	0.54	0.57	0.43	0.38	0.28	0.60	2.81
71	Washington County, RI	0.59	0.49	0.39	0.43	0.31	0.60	2.81
72	Cumberland County, NJ	0.54	0.51	0.38	0.41	0.33	0.64	2.80
73	New Hanover County, NC	0.53	0.53	0.43	0.41	0.30	0.60	2.80
74	Chesterfield County, VA	0.58	0.57	0.42	0.39	0.29	0.55	2.80
75	Rockingham County, NH	0.57	0.57	0.36	0.42	0.29	0.59	2.80
76	Northampton County, VA	0.51	0.48	0.46	0.39	0.29	0.67	2.80
77	Terrebonne Parish, LA	0.52	0.55	0.34	0.40	0.28	0.71	2.80
78	Erie County, OH	0.54	0.51	0.49	0.39	0.38	0.50	2.80
79	Dutchess County, NY	0.58	0.53	0.41	0.39	0.32	0.58	2.80
80	Henrico County, VA	0.59	0.58	0.34	0.40	0.34	0.55	2.80
81	Chautauqua County, NY	0.52	0.56	0.45	0.36	0.32	0.58	2.79

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
82	Somerset County, NJ	0.60	0.58	0.31	0.43	0.33	0.55	2.79
83	Suffolk County, NY	0.59	0.56	0.39	0.39	0.31	0.56	2.79
84	New Haven County, CT	0.57	0.55	0.37	0.40	0.34	0.56	2.79
85	Somerset County, MD	0.56	0.53	0.31	0.43	0.27	0.70	2.79
86	Knox County, ME	0.56	0.52	0.39	0.38	0.31	0.62	2.79
87	Delta County, MI	0.48	0.54	0.47	0.35	0.24	0.71	2.79
88	Marin County, CA	0.59	0.52	0.38	0.40	0.32	0.57	2.79
89	Galveston County, TX	0.51	0.50	0.46	0.43	0.31	0.57	2.78
90	Ascension Parish, LA	0.57	0.53	0.35	0.45	0.27	0.62	2.78
91	Barnstable County, MA	0.54	0.51	0.45	0.40	0.30	0.58	2.78
92	Delaware County, PA	0.59	0.53	0.44	0.38	0.35	0.50	2.78
93	Chowan County, NC	0.48	0.49	0.52	0.45	0.21	0.62	2.78
94	Camden County, NJ	0.56	0.52	0.41	0.39	0.36	0.53	2.77
95	Newport County, RI	0.56	0.49	0.40	0.40	0.33	0.60	2.77
96	LaPorte County, IN	0.54	0.54	0.36	0.40	0.35	0.58	2.77
97	Talbot County, MD	0.53	0.48	0.43	0.43	0.29	0.60	2.77
98	St. Clair County, MI	0.50	0.54	0.46	0.40	0.28	0.59	2.77
99	Middlesex County, MA	0.60	0.57	0.35	0.38	0.34	0.53	2.77
100	Ottawa County, MI	0.57	0.56	0.40	0.38	0.26	0.59	2.77
101	Currituck County, NC	0.53	0.58	0.25	0.45	0.28	0.68	2.77
102	Lake County, IL	0.60	0.55	0.38	0.38	0.29	0.57	2.77
103	Kauai County, HI	0.54	0.46	0.35	0.39	0.26	0.76	2.77
104	Huron County, MI	0.51	0.51	0.49	0.38	0.28	0.59	2.77
105	Beaufort County, NC	0.48	0.51	0.41	0.52	0.21	0.63	2.76
106	Monroe County, FL	0.51	0.50	0.42	0.38	0.28	0.67	2.76
107	York County, ME	0.54	0.53	0.41	0.39	0.28	0.61	2.76
108	Baltimore County, MD	0.58	0.58	0.36	0.39	0.31	0.54	2.76
109	Orleans County, NY	0.54	0.55	0.42	0.38	0.27	0.61	2.76
110	Bristol County, MA	0.56	0.51	0.40	0.39	0.31	0.59	2.76
111	Ontonagon County, MI	0.45	0.54	0.55	0.32	0.30	0.60	2.76
112	Norfolk County, MA	0.60	0.55	0.34	0.39	0.34	0.54	2.76
113	Iberia Parish, LA	0.55	0.50	0.41	0.42	0.27	0.60	2.76
114	Indian River County, FL	0.48	0.52	0.44	0.37	0.30	0.65	2.76
115	Monroe County, MI	0.53	0.52	0.39	0.47	0.28	0.56	2.75
116	Ocean County, NJ	0.55	0.55	0.38	0.42	0.27	0.59	2.75
117	Door County, WI	0.52	0.47	0.52	0.37	0.32	0.55	2.75
118	Nassau County, NY	0.61	0.56	0.44	0.38	0.36	0.40	2.75
119	Iosco County, MI	0.46	0.53	0.49	0.37	0.26	0.65	2.75
120	Calvert County, MD	0.58	0.53	0.35	0.44	0.26	0.58	2.75
121	Orange County, NY	0.58	0.55	0.34	0.39	0.31	0.58	2.75
122	Kent County, DE	0.52	0.56	0.34	0.41	0.28	0.63	2.75

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
123	Suffolk City, VA	0.59	0.52	0.29	0.41	0.30	0.64	2.74
124	Cuyahoga County, OH	0.54	0.55	0.44	0.39	0.38	0.45	2.74
125	Presque Isle County, MI	0.44	0.48	0.54	0.38	0.30	0.60	2.74
126	Pasquotank County, NC	0.53	0.50	0.37	0.43	0.29	0.62	2.74
127	Bergen County, NJ	0.58	0.55	0.34	0.41	0.37	0.49	2.74
128	Wayne County, NY	0.52	0.52	0.41	0.41	0.27	0.61	2.74
129	St. Bernard Parish, LA	0.52	0.48	0.36	0.47	0.23	0.68	2.74
130	Harford County, MD	0.57	0.55	0.37	0.40	0.27	0.57	2.74
131	Sagadahoc County, ME	0.56	0.56	0.34	0.38	0.27	0.62	2.74
132	Lane County, OR	0.53	0.55	0.43	0.38	0.27	0.58	2.74
133	Lake County, IN	0.55	0.51	0.39	0.39	0.36	0.53	2.74
134	King William County, VA	0.53	0.56	0.42	0.41	0.21	0.60	2.73
135	Dukes County, MA	0.54	0.49	0.42	0.43	0.26	0.59	2.73
136	Mackinac County, MI	0.45	0.54	0.44	0.33	0.34	0.63	2.73
137	Duval County, FL	0.55	0.54	0.39	0.35	0.32	0.57	2.73
138	Essex County, MA	0.56	0.48	0.39	0.39	0.31	0.59	2.73
139	Van Buren County, MI	0.53	0.53	0.38	0.42	0.25	0.61	2.72
140	Brevard County, FL	0.50	0.55	0.36	0.37	0.29	0.65	2.72
141	Atlantic County, NJ	0.53	0.48	0.33	0.42	0.33	0.63	2.72
142	James City County, VA	0.55	0.54	0.34	0.46	0.33	0.49	2.72
143	Hawaii County, HI	0.52	0.50	0.39	0.36	0.25	0.71	2.72
144	Essex County, VA	0.53	0.48	0.41	0.43	0.27	0.60	2.72
145	Ashtabula County, OH	0.51	0.51	0.40	0.39	0.31	0.59	2.72
146	Colleton County, SC	0.52	0.52	0.39	0.41	0.22	0.66	2.72
147	Westmoreland County, VA	0.51	0.49	0.47	0.41	0.23	0.60	2.71
148	Kenosha County, WI	0.56	0.54	0.32	0.39	0.30	0.59	2.71
149	Howard County, MD	0.62	0.59	0.29	0.39	0.29	0.54	2.71
150	Thurston County, WA	0.54	0.54	0.39	0.39	0.27	0.58	2.71
151	York County, VA	0.57	0.50	0.30	0.44	0.32	0.58	2.71
152	Stafford County, VA	0.58	0.56	0.32	0.39	0.28	0.57	2.71
153	Sussex County, DE	0.52	0.55	0.35	0.42	0.26	0.61	2.71
154	Martin County, FL	0.49	0.53	0.38	0.41	0.26	0.64	2.71
155	Horry County, SC	0.49	0.54	0.33	0.40	0.31	0.64	2.71
156	Hancock County, ME	0.56	0.49	0.38	0.37	0.29	0.62	2.71
157	Ashland County, WI	0.53	0.49	0.37	0.35	0.29	0.68	2.71
158	Providence County, RI	0.58	0.50	0.34	0.39	0.36	0.54	2.70
159	St. Johns County, FL	0.54	0.53	0.35	0.37	0.28	0.64	2.70
160	Bethel Census Area, AK	0.52	0.60	0.46	0.23	0.23	0.66	2.70
161	Middlesex County, NJ	0.57	0.57	0.32	0.40	0.35	0.50	2.70
162	Isle of Wight County, VA	0.53	0.48	0.45	0.43	0.20	0.61	2.70
163	Beaufort County, SC	0.51	0.50	0.32	0.44	0.27	0.66	2.70

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164	Glynn County, GA	0.50	0.48	0.35	0.39	0.31	0.67	2.70
165	Salem County, NJ	0.53	0.44	0.37	0.44	0.32	0.60	2.70
166	Livingston Parish, LA	0.57	0.53	0.40	0.41	0.22	0.56	2.70
167	Oswego County, NY	0.55	0.51	0.34	0.42	0.26	0.61	2.70
168	Accomack County, VA	0.53	0.53	0.36	0.41	0.19	0.68	2.70
169	Gogebic County, MI	0.51	0.50	0.41	0.33	0.28	0.66	2.70
170	Dillingham Census Area, AK	0.61	0.62	0.34	0.22	0.28	0.63	2.70
171	Calcasieu Parish, LA	0.57	0.49	0.34	0.40	0.29	0.60	2.70
172	Marinette County, WI	0.51	0.47	0.42	0.37	0.23	0.68	2.69
173	Georgetown County, SC	0.49	0.50	0.44	0.39	0.22	0.65	2.69
174	Hampton County, SC	0.50	0.54	0.43	0.41	0.18	0.64	2.69
175	Skagit County, WA	0.52	0.49	0.40	0.39	0.27	0.61	2.69
176	Whatcom County, WA	0.53	0.54	0.41	0.38	0.26	0.57	2.69
177	Dorchester County, SC	0.54	0.51	0.37	0.41	0.23	0.63	2.69
178	Anchorage Municipality, AK	0.58	0.54	0.30	0.34	0.29	0.63	2.69
179	Honolulu County, HI	0.55	0.49	0.35	0.39	0.30	0.61	2.69
180	Allegan County, MI	0.55	0.53	0.36	0.39	0.25	0.61	2.69
181	Cheboygan County, MI	0.47	0.49	0.49	0.34	0.25	0.65	2.69
182	Westchester County, NY	0.61	0.49	0.31	0.39	0.35	0.53	2.68
183	Chambers County, TX	0.52	0.53	0.32	0.41	0.29	0.61	2.68
184	Fairfax County, VA	0.59	0.60	0.27	0.38	0.30	0.54	2.67
185	Gloucester County, VA	0.53	0.50	0.36	0.41	0.24	0.62	2.67
186	Berkeley County, SC	0.54	0.51	0.36	0.39	0.22	0.64	2.67
187	Luce County, MI	0.48	0.45	0.52	0.33	0.26	0.63	2.67
188	Richmond County, VA	0.53	0.57	0.34	0.42	0.20	0.60	2.67
189	Cook County, IL	0.57	0.53	0.36	0.37	0.35	0.48	2.67
190	St. Mary's County, MD	0.58	0.59	0.33	0.43	0.25	0.49	2.67
191	Baldwin County, AL	0.52	0.55	0.35	0.38	0.32	0.53	2.67
192	Camden County, NC	0.53	0.54	0.28	0.40	0.23	0.69	2.66
193	Sonoma County, CA	0.55	0.51	0.33	0.40	0.30	0.57	2.66
194	Okaloosa County, FL	0.52	0.50	0.43	0.38	0.28	0.55	2.66
195	Surry County, VA	0.50	0.50	0.48	0.47	0.18	0.53	2.66
196	Washington County, ME	0.48	0.51	0.35	0.44	0.26	0.62	2.66
197	Lancaster County, VA	0.47	0.54	0.46	0.43	0.25	0.49	2.66
198	Harrison County, MS	0.49	0.46	0.34	0.40	0.34	0.61	2.66
199	Hertford County, NC	0.49	0.53	0.36	0.43	0.24	0.61	2.66
200	Cayuga County, NY	0.55	0.50	0.37	0.38	0.27	0.60	2.66
201	Kent County, MD	0.56	0.45	0.38	0.42	0.24	0.61	2.66
202	Porter County, IN	0.57	0.53	0.30	0.40	0.28	0.57	2.66
203	Pierce County, WA	0.54	0.52	0.38	0.37	0.30	0.54	2.66
204	Tangipahoa Parish, LA	0.52	0.51	0.40	0.42	0.27	0.53	2.65

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
205	Victoria County, TX	0.51	0.47	0.38	0.41	0.32	0.57	2.65
206	Nantucket County, MA	0.54	0.46	0.38	0.39	0.29	0.60	2.65
207	Taylor County, FL	0.48	0.55	0.38	0.40	0.26	0.58	2.65
208	Lafourche Parish, LA	0.55	0.46	0.37	0.40	0.25	0.63	2.65
209	Calhoun County, TX	0.50	0.49	0.37	0.41	0.25	0.61	2.64
210	Virginia Beach City, VA	0.57	0.53	0.33	0.40	0.27	0.55	2.64
211	Washington County, NC	0.44	0.46	0.45	0.43	0.21	0.65	2.64
212	Tuscola County, MI	0.51	0.50	0.38	0.42	0.23	0.60	2.64
213	St. Martin Parish, LA	0.55	0.44	0.40	0.41	0.21	0.63	2.64
214	Orange County, TX	0.48	0.50	0.40	0.38	0.25	0.62	2.64
215	Craven County, NC	0.50	0.48	0.29	0.45	0.26	0.65	2.64
216	Volusia County, FL	0.49	0.54	0.34	0.38	0.25	0.64	2.64
217	Hillsborough County, FL	0.55	0.56	0.27	0.39	0.30	0.57	2.64
218	Humboldt County, CA	0.50	0.49	0.40	0.36	0.30	0.58	2.64
219	Brunswick County, NC	0.46	0.52	0.30	0.45	0.26	0.65	2.64
220	Grand Traverse County, MI	0.55	0.60	0.31	0.37	0.31	0.50	2.63
221	Menominee County, MI	0.50	0.49	0.34	0.36	0.24	0.71	2.63
222	St. Lucie County, FL	0.49	0.51	0.31	0.44	0.28	0.59	2.63
223	Escambia County, FL	0.52	0.51	0.39	0.38	0.32	0.51	2.63
224	San Mateo County, CA	0.57	0.55	0.23	0.39	0.33	0.56	2.63
225	Wayne County, MI	0.52	0.56	0.36	0.39	0.37	0.44	2.63
226	Mathews County, VA	0.44	0.46	0.49	0.45	0.20	0.59	2.63
227	Santa Cruz County, CA	0.55	0.49	0.33	0.41	0.28	0.57	2.63
228	Prince William County, VA	0.58	0.56	0.29	0.38	0.28	0.55	2.63
229	Fairfield County, CT	0.57	0.49	0.29	0.39	0.33	0.56	2.63
230	Pamlico County, NC	0.46	0.53	0.32	0.46	0.18	0.68	2.63
231	Macomb County, MI	0.53	0.56	0.36	0.39	0.28	0.51	2.63
232	Chippewa County, MI	0.48	0.45	0.38	0.35	0.29	0.68	2.63
233	Manistee County, MI	0.50	0.50	0.37	0.37	0.28	0.61	2.63
234	Keweenaw County, MI	0.48	0.49	0.43	0.30	0.38	0.55	2.62
235	Prince George's County, MD	0.57	0.59	0.25	0.38	0.30	0.53	2.62
236	Ketchikan Gateway Borough, AK	0.55	0.54	0.30	0.33	0.28	0.64	2.62
237	Baraga County, MI	0.51	0.52	0.37	0.33	0.25	0.64	2.62
238	Solano County, CA	0.55	0.52	0.30	0.40	0.28	0.58	2.62
239	Waldo County, ME	0.50	0.51	0.35	0.38	0.25	0.62	2.62
240	Bay County, FL	0.49	0.53	0.40	0.40	0.30	0.51	2.62
241	Carteret County, NC	0.48	0.50	0.39	0.40	0.23	0.60	2.62
242	Charlevoix County, MI	0.51	0.52	0.45	0.35	0.25	0.53	2.61
243	San Francisco County, CA	0.58	0.53	0.23	0.38	0.35	0.54	2.61
244	Cecil County, MD	0.55	0.53	0.27	0.42	0.27	0.58	2.61
245	Santa Rosa County, FL	0.52	0.46	0.38	0.39	0.26	0.61	2.61

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
246	Maui County, HI	0.55	0.48	0.32	0.39	0.30	0.58	2.61
247	Pender County, NC	0.50	0.52	0.28	0.43	0.21	0.67	2.61
248	Broward County, FL	0.54	0.54	0.25	0.35	0.28	0.65	2.61
249	Charlotte County, FL	0.41	0.55	0.33	0.40	0.28	0.64	2.60
250	Arenac County, MI	0.47	0.52	0.43	0.38	0.23	0.57	2.60
251	Northwest Arctic Borough, AK	0.53	0.45	0.55	0.20	0.23	0.64	2.60
252	Middlesex County, VA	0.48	0.47	0.48	0.39	0.19	0.59	2.60
253	Houghton County, MI	0.54	0.52	0.39	0.33	0.29	0.53	2.60
254	Mason County, MI	0.51	0.51	0.37	0.37	0.24	0.61	2.60
255	Norfolk City, VA	0.56	0.43	0.28	0.40	0.41	0.51	2.60
256	Lincoln County, ME	0.52	0.50	0.39	0.38	0.27	0.53	2.60
257	Sanilac County, MI	0.48	0.48	0.41	0.39	0.24	0.59	2.60
258	Alexandria City, VA	0.60	0.53	0.26	0.38	0.43	0.40	2.60
259	Mendocino County, CA	0.49	0.48	0.43	0.38	0.26	0.57	2.59
260	Clay County, FL	0.54	0.56	0.38	0.38	0.26	0.48	2.59
261	Ventura County, CA	0.56	0.48	0.34	0.38	0.27	0.55	2.59
262	Union County, NJ	0.56	0.51	0.31	0.39	0.38	0.44	2.59
263	Snohomish County, WA	0.54	0.53	0.31	0.37	0.27	0.56	2.58
264	Refugio County, TX	0.48	0.46	0.50	0.41	0.26	0.48	2.58
265	Los Angeles County, CA	0.55	0.51	0.32	0.37	0.32	0.52	2.58
266	Juneau City and Borough, AK	0.57	0.54	0.26	0.33	0.26	0.63	2.58
267	Nassau County, FL	0.50	0.57	0.26	0.40	0.24	0.61	2.58
268	Contra Costa County, CA	0.56	0.53	0.29	0.38	0.30	0.53	2.58
269	District of Columbia, DC	0.60	0.56	0.44	0.23	0.40	0.35	2.58
270	Liberty County, FL	0.51	0.56	0.33	0.39	0.11	0.67	2.58
271	Cameron County, TX	0.47	0.55	0.33	0.42	0.22	0.58	2.58
272	Hernando County, FL	0.47	0.56	0.40	0.38	0.25	0.52	2.58
273	Monterey County, CA	0.56	0.43	0.34	0.39	0.28	0.58	2.58
274	Charles City County, VA	0.49	0.43	0.47	0.40	0.17	0.62	2.57
275	King George County, VA	0.57	0.48	0.27	0.40	0.27	0.59	2.57
276	Matagorda County, TX	0.47	0.47	0.39	0.43	0.23	0.58	2.57
277	Strafford County, NH	0.56	0.51	0.24	0.39	0.29	0.59	2.57
278	Bristol County, RI	0.61	0.46	0.37	0.41	0.29	0.44	2.57
279	Santa Barbara County, CA	0.56	0.45	0.31	0.38	0.29	0.59	2.57
280	Hopewell City, VA	0.52	0.49	0.38	0.40	0.40	0.37	2.56
281	Jefferson Davis Parish, LA	0.53	0.46	0.41	0.42	0.26	0.48	2.56
282	Alameda County, CA	0.58	0.54	0.23	0.37	0.32	0.52	2.56
283	Citrus County, FL	0.44	0.53	0.43	0.41	0.21	0.54	2.56
284	Pacific County, WA	0.43	0.47	0.39	0.43	0.26	0.58	2.56
285	Vermilion Parish, LA	0.54	0.43	0.35	0.41	0.25	0.57	2.55
286	King and Queen County, VA	0.54	0.41	0.40	0.41	0.18	0.63	2.55

	County	Social	Economic	Community Capital	Institutional	Housing/ Infrastructural	Environmental	Total Resilience
287	Jefferson County, FL	0.49	0.55	0.42	0.41	0.16	0.53	2.55
288	Wayne County, GA	0.51	0.46	0.34	0.39	0.20	0.65	2.55
289	Collier County, FL	0.49	0.48	0.28	0.37	0.27	0.66	2.55
290	San Patricio County, TX	0.47	0.44	0.33	0.49	0.25	0.57	2.55
291	King County, WA	0.57	0.55	0.23	0.34	0.31	0.54	2.55
292	Clatsop County, OR	0.52	0.48	0.29	0.40	0.30	0.55	2.55
293	Poquoson City, VA	0.53	0.45	0.38	0.42	0.23	0.53	2.55
294	Portsmouth City, VA	0.55	0.46	0.37	0.40	0.36	0.40	2.55
295	Wakulla County, FL	0.53	0.53	0.30	0.39	0.20	0.60	2.55
296	Grays Harbor County, WA	0.48	0.51	0.30	0.40	0.27	0.58	2.54
297	Suffolk County, MA	0.58	0.53	0.26	0.38	0.44	0.36	2.54
298	Bryan County, GA	0.55	0.50	0.27	0.41	0.24	0.57	2.54
299	Antrim County, MI	0.48	0.52	0.43	0.35	0.23	0.53	2.54
300	Hampton City, VA	0.54	0.49	0.27	0.41	0.34	0.49	2.54
301	Assumption Parish, LA	0.49	0.47	0.40	0.41	0.16	0.61	2.54
302	Jefferson County, NY	0.56	0.44	0.27	0.38	0.30	0.60	2.54
303	Benzie County, MI	0.50	0.53	0.37	0.38	0.26	0.51	2.54
304	Douglas County, WI	0.52	0.53	0.30	0.36	0.26	0.57	2.54
305	Santa Clara County, CA	0.57	0.52	0.22	0.37	0.31	0.53	2.54
306	Nome Census Area, AK	0.56	0.43	0.46	0.22	0.24	0.62	2.54
307	Caroline County, MD	0.54	0.49	0.31	0.44	0.24	0.52	2.54
308	Caroline County, VA	0.55	0.48	0.27	0.41	0.24	0.59	2.53
309	Jefferson County, WA	0.46	0.56	0.30	0.40	0.24	0.57	2.53
310	Bertie County, NC	0.47	0.47	0.41	0.42	0.12	0.64	2.53
311	Richmond County, NY	0.57	0.53	0.39	0.32	0.30	0.42	2.53
312	San Diego County, CA	0.56	0.51	0.28	0.34	0.29	0.55	2.53
313	Sarasota County, FL	0.47	0.54	0.35	0.37	0.28	0.51	2.53
314	Kitsap County, WA	0.53	0.50	0.40	0.39	0.27	0.45	2.53
315	McIntosh County, GA	0.46	0.56	0.32	0.38	0.19	0.61	2.53
316	Franklin County, FL	0.49	0.45	0.42	0.40	0.28	0.47	2.52
317	Miami-Dade County, FL	0.52	0.48	0.15	0.38	0.29	0.70	2.52
318	Perquimans County, NC	0.47	0.40	0.33	0.49	0.19	0.62	2.52
319	Orange County, CA	0.57	0.55	0.29	0.35	0.30	0.46	2.52
320	Kenai Peninsula Borough, AK	0.53	0.49	0.28	0.34	0.25	0.63	2.52
321	Palm Beach County, FL	0.52	0.51	0.25	0.35	0.27	0.62	2.52
322	Walton County, FL	0.49	0.54	0.33	0.40	0.33	0.43	2.51
323	Bayfield County, WI	0.47	0.45	0.48	0.34	0.26	0.51	2.51
324	Manatee County, FL	0.49	0.54	0.26	0.37	0.26	0.59	2.51
325	Hancock County, MS	0.49	0.54	0.24	0.41	0.28	0.55	2.50
326	Gates County, NC	0.48	0.51	0.30	0.42	0.14	0.65	2.50
327	Prince George County, VA	0.55	0.50	0.19	0.41	0.26	0.59	2.50

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328	Alcona County, MI	0.42	0.56	0.33	0.35	0.21	0.63	2.50
329	Jasper County, SC	0.50	0.47	0.26	0.40	0.21	0.66	2.50
330	Gulf County, FL	0.47	0.55	0.31	0.42	0.26	0.48	2.50
331	Camden County, GA	0.54	0.44	0.20	0.39	0.25	0.67	2.49
332	Iron County, WI	0.47	0.43	0.36	0.33	0.28	0.62	2.49
333	Flagler County, FL	0.44	0.51	0.36	0.38	0.22	0.57	2.49
334	Jones County, NC	0.42	0.50	0.31	0.46	0.15	0.65	2.49
335	Lake and Peninsula Borough, AK	0.48	0.51	0.30	0.23	0.31	0.67	2.48
336	Pinellas County, FL	0.51	0.56	0.31	0.38	0.28	0.43	2.48
337	Oceana County, MI	0.50	0.52	0.37	0.37	0.22	0.51	2.48
338	Matanuska-Susitna Borough, AK	0.54	0.49	0.21	0.34	0.26	0.64	2.48
339	Essex County, NJ	0.54	0.47	0.25	0.39	0.38	0.46	2.48
340	Jackson County, MS	0.50	0.45	0.29	0.42	0.30	0.50	2.47
341	Tyrrell County, NC	0.46	0.45	0.34	0.40	0.17	0.65	2.47
342	Pasco County, FL	0.51	0.54	0.27	0.36	0.23	0.54	2.46
343	Baltimore City, MD	0.57	0.54	0.36	0.25	0.44	0.30	2.46
344	Mason County, WA	0.46	0.54	0.27	0.40	0.22	0.57	2.46
345	Clallam County, WA	0.47	0.52	0.37	0.38	0.24	0.48	2.45
346	Philadelphia County, PA	0.53	0.52	0.31	0.37	0.46	0.27	2.45
347	Douglas County, OR	0.49	0.49	0.31	0.37	0.23	0.56	2.45
348	Northumberland County, VA	0.51	0.42	0.42	0.40	0.20	0.49	2.45
349	Jackson County, TX	0.45	0.44	0.41	0.41	0.27	0.46	2.45
350	Lee County, FL	0.49	0.52	0.28	0.36	0.27	0.53	2.44
351	Brantley County, GA	0.53	0.55	0.30	0.38	0.09	0.58	2.44
352	Putnam County, FL	0.49	0.53	0.28	0.37	0.14	0.62	2.44
353	San Juan County, WA	0.50	0.47	0.37	0.37	0.26	0.47	2.44
354	Onslow County, NC	0.52	0.39	0.24	0.40	0.26	0.64	2.44
355	Liberty County, GA	0.55	0.44	0.19	0.38	0.23	0.66	2.44
356	Hyde County, NC	0.49	0.37	0.26	0.46	0.22	0.63	2.43
357	Aransas County, TX	0.39	0.41	0.37	0.44	0.24	0.58	2.43
358	Alger County, MI	0.52	0.42	0.30	0.37	0.26	0.55	2.42
359	Williamsburg City, VA	0.59	0.40	0.24	0.59	0.35	0.25	2.41
360	Harris County, TX	0.51	0.55	0.28	0.31	0.32	0.44	2.41
361	Kodiak Island Borough, AK	0.54	0.39	0.23	0.34	0.26	0.64	2.41
362	Newport News City, VA	0.54	0.48	0.35	0.43	0.32	0.28	2.40
363	Willacy County, TX	0.47	0.45	0.22	0.44	0.23	0.58	2.40
364	Kleberg County, TX	0.50	0.37	0.37	0.38	0.28	0.47	2.38
365	Prince of Wales-Hyder Census Area, AK	0.40	0.49	0.54	0.12	0.20	0.63	2.37
366	Tillamook County, OR	0.47	0.43	0.37	0.37	0.28	0.45	2.37
367	Charlton County, GA	0.46	0.51	0.19	0.40	0.12	0.67	2.37

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368	Levy County, FL	0.45	0.52	0.37	0.41	0.13	0.48	2.35
369	Lincoln County, OR	0.44	0.52	0.27	0.42	0.26	0.44	2.35
370	Sitka City and Borough, AK	0.56	0.43	0.26	0.30	0.31	0.51	2.35
371	Yakutat City and Borough, AK	0.53	0.48	0.24	0.34	0.25	0.50	2.35
372	New York County, NY	0.56	0.53	0.23	0.37	0.40	0.27	2.35
373	Island County, WA	0.49	0.44	0.32	0.38	0.25	0.47	2.35
374	Kalawao County, HI	0.57	0.63	0.48	0.31	0.34	0.00	2.34
375	Kusilvak Census Area, AK	0.48	0.49	0.50	0.12	0.18	0.54	2.32
376	Bristol Bay Borough, AK	0.51	0.39	0.16	0.25	0.38	0.62	2.32
377	Wahkiakum County, WA	0.39	0.45	0.33	0.43	0.22	0.49	2.31
378	Curry County, OR	0.47	0.49	0.24	0.37	0.25	0.47	2.28
379	Coos County, OR	0.47	0.46	0.24	0.36	0.26	0.48	2.27
380	Del Norte County, CA	0.52	0.47	0.19	0.40	0.22	0.47	2.27
381	Hudson County, NJ	0.54	0.46	0.15	0.38	0.43	0.28	2.24
382	Wrangell City and Borough, AK	0.52	0.46	0.18	0.20	0.27	0.59	2.24
383	Dixie County, FL	0.47	0.54	0.26	0.40	0.08	0.49	2.23
384	Haines Borough, AK	0.49	0.35	0.17	0.31	0.27	0.65	2.23
385	Arlington County, VA	0.61	0.57	0.24	0.38	0.34	0.09	2.23
386	Petersburg Borough, AK	0.52	0.39	0.13	0.20	0.29	0.63	2.17
387	Queens County, NY	0.54	0.48	0.18	0.29	0.34	0.32	2.15
388	Aleutians East Borough, AK	0.47	0.46	0.21	0.20	0.17	0.64	2.15
389	Kings County, NY	0.53	0.48	0.25	0.28	0.33	0.26	2.12
390	Skagway Municipality, AK	0.50	0.45	0.05	0.24	0.25	0.63	2.11
391	Aleutians West Census Area, AK	0.56	0.48	0.02	0.23	0.21	0.61	2.11
392	Kenedy County, TX	0.33	0.28	0.45	0.27	0.36	0.38	2.07
393	Copper River Census Area, AK	0.54	0.57	0.21	0.00	0.25	0.50	2.06
394	Bronx County, NY	0.48	0.40	0.20	0.30	0.36	0.29	2.04
395	Chugach Census Area, AK	0.55	0.55	0.14	0.00	0.28	0.50	2.02
396	Hoonah-Angoon Census Area, AK	0.36	0.40	0.16	0.15	0.21	0.64	1.93
397	North Slope Borough, AK	0.55	0.45	0.19	0.18	0.20	0.33	1.91

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