

Community Resilience Indicator Analysis:

Commonly Used Indicators from Peer-Reviewed Research: Updated for Research Published 2003-2021

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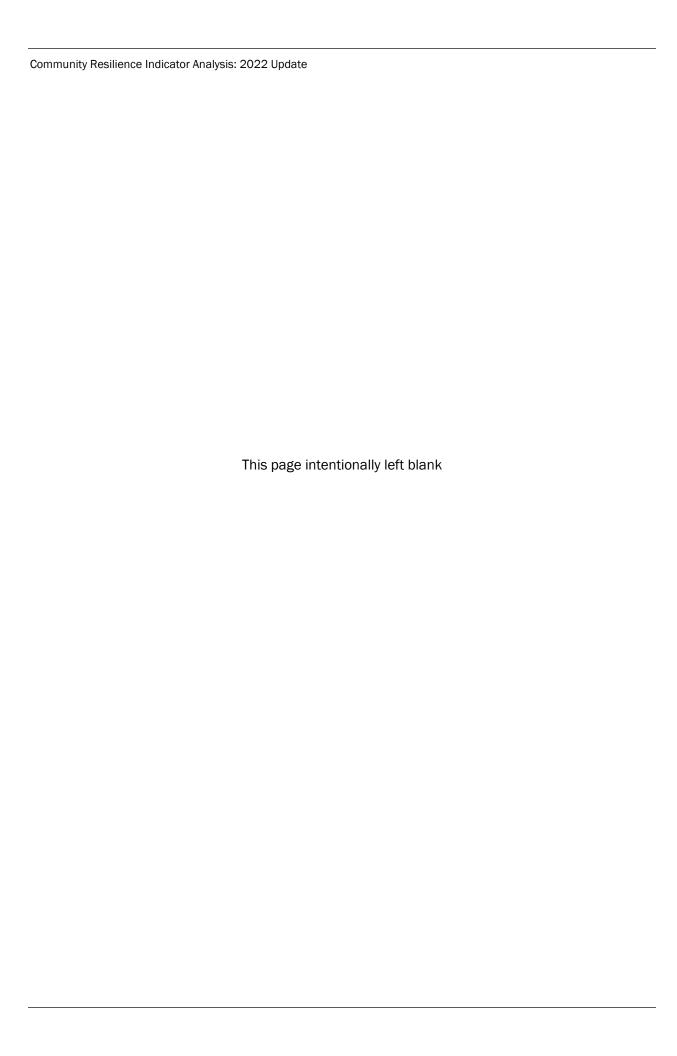


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1. Overview

In 2017, FEMA's National Integration Center (NIC) Technical Assistance (TA) Branch identified a need to establish a data-driven basis for prioritizing locations for TA investment and guiding local emergency management planning. To achieve this goal, FEMA tasked Argonne National Laboratory (Argonne) with identifying commonly used indicators of community resilience across the landscape of published peer-reviewed research.

FEMA and Argonne completed the first Community Resilience Indicator Analysis (CRIA) in 2018 and repeated the process in 2022. The CRIA process begins with a literature review and cataloguing of published peer-reviewed assessment methodologies on social vulnerability and community resilience. The literature review findings are then filtered by inclusion criteria established by the CRIA research team to ensure the methodologies are:

- Quantitative,
- Data and methodology are publicly available,
- Calculated at the county level or lower,
- Examine generalized hazard risk (rather than a singular hazard), and
- Focused on pre-disaster community conditions.

After this, the research team identifies the commonly used indicators across these methodologies and selects the best data source for each indicator. Finally, the research team bins the data for visual display, conducts a correlation analysis and creates a composite index, the FEMA Community Resilience Index (FEMA CRI).

In 2018, the CRIA identified eight resilience and vulnerability assessment methodologies and 20 commonly used indicators (indicators used in three or more of the eight methodologies). The FEMA CRI in 2018 was created from these 20 indicators and was produced for at the county level. The 2022 CRIA updated the literature review to expand the list of methodologies examined and followed the same process, resulting in an analysis of 14 methodologies published between 2003 and 2021 and 22 indicators¹ identified as commonly used (indicators used in five or more of the 14 methodologies). In 2022, the research team produced the FEMA CRI at the county and the census tract levels.

¹ Five indicators were added to the list in 2022, and three indicators were retired from the 2018 list.

To make the CRIA data more accessible and more actionable, each individual indicator and the FEMA CRI is binned and included in FEMA's Resilience Analysis and Planning Tool (RAPT).² RAPT enables emergency managers and community partners to quickly visualize relative differences in potential resilience by county, tribe and census tract.

By reviewing the data for each of these 22 indicators individually, emergency managers can gain insights for targeted outreach strategies, planning, mitigation investments and response and recovery operations. Communities, regional governments and others can use this data to better understand potential challenges to resilience. As the social science field of examining and validating indicators of resilience evolves, FEMA will update RAPT to provide emergency managers and community partners with additional data and tools to inform planning, mitigation, response and recovery.

It is important to understand that the role of the emergency manager is not to change or to "improve" the data, but to plan appropriately for the community characteristics reflected in the data. These datasets are community characteristics that researchers have identified as important considerations for resilience. For example, people with disabilities may have greater challenges to be resilient to disasters. If a community has a high population of people with disabilities, the emergency manager(s) may need to create tailored preparedness outreach programs and strategies to ensure those residents have support if evacuation is necessary.

Rather than label these indicators as an absolute measure of resilience, FEMA considers "potential challenges to resilience" a better frame to understand these indicators. Everyone is vulnerable to disasters. While scholars theorize that certain characteristics may make an individual or a household more socially vulnerable (and less resilient), the data does not reflect measures that individuals and/or communities have taken to address potential challenges, such as emergency management planning and outreach or household preparedness measures. To aid emergency managers in understanding how to use these indicators, calling them potential challenges to resilience supports a more positive and strategic application of the data in all phases of emergency management.

2. 2018 CRIA Summary

To identify the set of methodologies for the first CRIA, Argonne catalogued peer-reviewed methodologies cited in meta-analyses of community resilience published between 2013-2017. The research team then selected the methodologies that met the following inclusion criteria.

 Quantitative measures: To ensure that indicators could be easily compared across methodologies, the team only included methodologies that used exclusively quantitative measures.

² RAPT is a free, online, geographic information system (GIS) tool with data layers on population characteristics, infrastructure and hazards. RAPT is designed to support all phases of emergency management. Access RAPT here: www.fema.gov/rapt.

- Publicly available methodology: For the analysis and findings to be transparent, the team only included methodologies that were publicly available.
- Public data source: To ensure transparency, replicability and updates over time, indicator data had to be from publicly available secondary sources, such as the U.S. Census and the Bureau of Labor Statistics.
- At least county-level unit of analysis: The team only included studies where the unit of analysis was, or could be easily adapted to, a U.S. county. Although more granularity offers greater clarity, many studies do not include data below the county level.
- Generalized risk: Because the NIC provides technical assistance relative to a wide range of hazards, the inclusion criteria retained methodologies that applied to multiple hazards. Methodologies that focused on one specific risk (such as earthquakes, food security, poverty or public health) were included in the CRIA analysis. Although these studies offer insights for these topic areas, studies with an all-hazards perspective were more appropriate for comparative purposes.
- Pre-disaster conditions: As NIC TA supports communities to build resilience prior to a disaster,
 the research team focused on community characteristics present before an incident occurred.

Using these inclusion criteria as a filter, the research team identified eight methodologies for further analysis in 2018. The names of some methodologies highlight social vulnerability and some highlight community resilience. While community resilience encompasses more than population characteristics, the research team drew from methodologies with either focus to capture the broadest research set. The research team also included methodologies from developed countries other than the United States.

After cataloguing more than 100 unique indicators used across the eight methodologies, the team identified 20 indicators that were used in three or more of these methodologies. Identifying indicators used in multiple methodologies suggests researcher agreement on the importance of these indicators.

Argonne then selected datasets from the U.S. Census American Community Survey (ACS) five-year estimates and other public data sources for the 20 indicators, binned the data and created GIS data layers to include in RAPT. The five-year estimate provides greater statistical reliability of population and community characteristics than one-year data, especially for smaller geographic areas. In addition to the individual data layers, FEMA and Argonne created the FEMA CRI at the county level using standard deviation to calculate the spread of values for the country.

The first CRIA Report, released in December 2018, used data from the 2012-2016 ACS 5-year estimates. FEMA updated the indicator data with the ACS 5-year estimates from 2013-2017 in the November 2019 RAPT release. In March 2020, FEMA updated RAPT with ACS 5-year estimates for 2015-2019.

3. 2022 CRIA Summary

3.1. Literature Review and Selected Methodologies

To capture the most current community resilience research, FEMA conducted another literature review in 2021 to identify peer-reviewed articles published from 2018-2021.

The literature review was conducted via a Web of Science library search using the search terms: "resilience" and "index, methodology(ies), or indicator(s)" and "community or disaster." The 2021 literature search identified 2,151 records. Argonne reviewed the abstracts for all records and selected articles that discussed resilience assessment methodologies not included in the 2018 analysis. The team then compared the resulting 17 articles against the CRIA inclusion criteria to identify additional methodologies for analysis.

<u>Appendix A</u> includes the comprehensive list of over 90 methodologies identified from the 2018 and 2021 literature reviews. The <u>table</u> includes the methodologies names, dates of publication, a link to the methodology reports or developers and a determination for each CRIA inclusion criterion.

Combining the findings from both literature reviews, 14 methodologies met the CRIA inclusion criteria. Full citations for these methodologies are included in Appendix B.

The methodologies met the inclusion criteria from the 2022 literature review:

- Fraser: Japanese Social Capital and Social Vulnerability Indices
- Nursey-Bray: Indicators for Adaptive Capacity
- Regional Climate Resilience Index (RCRI)
- Composite Community Disaster Resilience Index (CCDRI)
- Comprehensive Disaster Resilience Index (CDRI2)
- Social Vulnerability Index (SoVI)

The following methodologies met the inclusion criteria from the 2018 literature review:

- Australian National Disaster Resilience Index (ANDRI)
- Baseline Resilience Indicators for Communities (BRIC)
- Community Disaster Resilience Index (CDRI)
- Community Resilience Index (CRI2)
- Disaster Resilience of Place (DROP)
- Resilient Capacity Index (RCI)
- Social Vulnerability Index (SVI)
- The Composite Resilience Index (TCRI)

3.2. Commonly Used Indicators and Data Sources

To identify the commonly used indicators across the 2022 CRIA set of 14 methodologies, the team first documented all the indicators used in each of the six newly identified methodologies (157 in

total) and added them to the list of the indicators from the 2018 CRIA methodologies. The research team then established the threshold of commonly used indicators as those used in five or more of the 14 methodologies. This analysis resulted in identifying 22 common indicators. The research team also documented citations from the methodologies' authors that explained their reasoning for using the indicators.

The following <u>table</u> lists the 22 indicators and references how many of the 14 methodologies used that indicator. Five indicators that were not on the 2018 list have been added: inactive voters, unemployed women, workforce employed in the dominant sector, households with a smartphone and population below poverty level. Three indicators were retired from the list because there were not used in at least five methodologies (listed in *blue* italics): public school capacity, rental property capacity and hotel/motel capacity.

Table 1: 2022 CRIA Indicators

Commonly Used Indicators	Number of Methodologies Using this Indicator (of 14)
Unemployed labor force	13
Population without a high school diploma	11
Percent of inactive voters*	10
Households without a vehicle	9
Number of hospitals	9
Population age 65 and older	9
Medical professional capacity	8
Population with a disability	7
Households with limited English	7
Single-parent households	7
Population without health insurance	7
Unemployed women labor force*	7
Presence of civic and social organizations	6
Median household income	6
Income inequality	6
Population change	6
Population without religious affiliation	6
Mobile homes as percentage of housing	6
Owner-occupied housing	6
Workforce in predominant sector*	5
Households without a smartphone*	5
Population below poverty level*	5
Public school capacity	4
Rental property capacity	4
Hotel/motel capacity	3

Indicators added in 2022 are marked with an asterisk "*"

Indicators in *blue italics* were included in the 2018 CRIA but are not used in at least five of the 2022 CRIA methodologies

After identifying the 22 commonly used indicators, the research team selected the most authoritative data source for each indicator metric. Most of the indicators related to population and community characteristics are available from the U.S. Census Bureau. When available, the research team selected datasets for U.S. counties, census tracts and tribes.

To assist emergency managers with analyzing their community, the research team grouped the 22 2022 CRIA Indicators into six categories:

Population Characteristics

- Population without a High School Education
- Population 65 and Older
- Population with a Disability

Household Characteristics

- Households without a Vehicle
- Households with Limited English
- Single-Parent Households
- Households without a Smartphone

Housing

- Mobile Homes as Percentage of Housing
- Owner-Occupied Housing

Healthcare

- Number of Hospitals*
- Medical Professional Capacity*
- Population without Health Insurance

Economic

- Population Below Poverty Level
- Median Household Income
- Unemployed Labor Force
- Unemployed Women Labor Force
- Income Inequality+
- Workforce in Predominant Sector

Connection to Community

- Presence of Civic and Social Organizations*
- Population with Religious Affiliation*
- Percent of Inactive Voters*
- Population Change*

Census tract data is available for all indicators, except:

- * Indicates County level data only,
- + Indicates County and Tribal level data only

3.3. Data Binning

With such large datasets, binning the data and assigning consistent color ramps for the bins provides a visual cue to quickly grasp a data range. While the specific datapoint for the geography (county, census tract or tribe) is also available, the bins provide a more immediate high-level understanding of a geographic area's characteristics.

To bin each dataset for mapping, Argonne used the Python Spatial Analysis Library, PySAL, and its Exploratory Spatial Data Analysis sub-package. Python is an open-source, high-level programming language that is used in social science research. The package includes nine binning methods. Rather than make arbitrary "breaks" in the data, these binning methods allowed the research team to use the best binning method that would group data that are close in value to each other and maximize the variance between bins.

The team evaluated which of the nine binning methods 1) best fit the relationships of the breaks to each dataset's means and medians and 2) could be consistently replicated. This analysis identified four binning methods as the best fit for most datasets. For the county-level datasets, the research team binned the dataset into five bins. For the indicators with census tract data, the research team binned the dataset into seven bins, allowing greater differentiation with these substantially larger datasets.

The binning methods for the 22 commonly used indicators are:

- **Fisher–Jenks Breaks:** This method aims to return class breaks such that classes are internally homogenous while assuring heterogeneity among classes. The Python toolkit calculates squared deviations against class means.
- Jenks-Caspall Breaks: This method aims to minimize the absolute deviation from within-class medians. Python's calculation focuses on within-class absolute deviations from the median.
- Head/Tail Breaks: Algorithmically optimal breaks and the number of classes are based on the dataset itself. The Head/Tails Breaks method works well with heavily tailed datasets, iterating through the data to minimize around the mean.³
- Other: In specific cases, the team used alternative criteria to select binning methodologies.
 - Income: A convention for displaying income data already exists: \$0-20,000, \$20,001-\$40,000, etc. (an intuitive methodology similar to equal intervals).
 - Population Change: The population change dataset is provided by the U.S. Census as "net migration," which provides a positive (increase in population) or negative (decrease in population) number.⁴ Large population changes in either direction could cause challenges to resilience. The team chose to represent the population change data as standard deviations from zero, where less change is preferred to more change (regardless of whether the change is positive or negative).

Appendix C provides the indicator, data source, national average, binning method and other information about each of the 22 indicators. In the 2022 release of RAPT, all datasets drawing from the U.S. Census are from the 2016-2020 ACS 5-year estimates and the census tract boundaries are the updated boundaries from the 2020 Decennial Census. FEMA will update RAPT with new ACS data annually as new U.S. Census data is released.

3.4. Correlation Analysis

The research team conducted a correlation analysis to measure and describe the strength and direction of the relationships among the 22 commonly used community resilience indicators. The correlation analysis shows how individual indicators may be related to each other. Understanding these correlations helps communities design resilience strategies that take these relationships into account.

The Pearson Correlation Coefficient is a numerical measure of linear correlation from −1 to 1.

³ Jiang, B., 2013, Head/tail Breaks: A New Classification Scheme for Data with a Heavy-tailed Distribution. The Professional Geographer, 65, 482-494.

⁴ U.S. Census Bureau. https://www.census.gov/glossary/#term_Netmigration, accessed March 28, 2022.

- A coefficient closer to 1 indicates a positive correlation (variable A increases as variable B increases).
- A coefficient of 0 indicates no correlation.
- A coefficient closer to -1 indicates a negative correlation (variable A increases as variable B decreases).

As jurisdictions consider strategies to address indicator metrics that reveal challenges to resilience, the correlation analysis helps identify populations that may face multiple challenges concurrently. For example, there is a high correlation between individuals that are unemployed and those that are more likely to speak a language other than English and be without access to a vehicle. Outreach to these populations should consider all three of these characteristics.

The full chart of Pearson Correlation Coefficients can be found in Appendix D.

3.5. FEMA Community Resilience Index (CRI)

The research team developed a process to create a composite index comprised of the 22 commonly used indicators, the FEMA CRI. This index provides a relative composite value by county and by census tract, measured as an average of counts of standard deviations from the national mean for each indicator. The 2022 FEMA CRI uses the most currently available census data, the 2016-2020 ACS 5-year estimates, and will be updated annually.

To produce the CRI, the team first oriented all the datasets in the same direction (higher number represents higher resilience) and then converted each county and census tracts' data point to a standardized score value based on standard deviations above or below the indicator's national mean (except for population change calculated as standard deviations from zero). The team then averaged the 22 standardized score values for each county and census tract to create the FEMA CRI value. Because there is no validated method for weighting resilience indicators, the research team did not weight individual indicators in developing the FEMA CRI.

- County CRI: When data for an indicator was not available for a given county, the team used the national mean for that indicator; this approach does not artificially push an aggregate indicator more positive or more negative. Though the team examined linear and non-linear models, they determined that using the national mean for missing county data, the simplest solution, was the best solution.
- Census Tract CRI: When data for an indicator was not available at the census tract level, the research team imputed the county data for the census tract calculation.

The FEMA CRI process produces a numerical standard deviation data point for each county and each census tract. As with the indicator datasets, the FEMA CRI is binned into five bins for the county and seven bins for the census tract and are included in RAPT. Including the CRIA data in RAPT allows users to view both the composite index and datapoints for each indicator comprising the index to better understand the drivers behind the composite index values.

3.6. Future Research

As the social science of community resilience continues to evolve, additional analysis could evaluate the usefulness of weighting the indicators, validating the indicators, examining specific indicators by risk and adding or retiring indicators. Principal component analysis, factor analysis, regression analysis, or structured sensitivity analysis could provide findings on the relative importance and weight of an indicator's contribution to overall resilience. It may also be of interest to examine how these indicators may have different impacts in rural versus urban areas or differences by region.

The researchers involved in developing the CRIA process, the FEMA CRI and RAPT continue to look for opportunities to evaluate the validity and usefulness of this set of indicators with the goal of ensuring that the data is easily accessible and a useful focusing tool for initial situational awareness for preparedness, mitigation, response and recovery efforts.

Appendix A: Reviewed Methodologies for the 2022 Community Resilience Indicator Analysis (CRIA)

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
Hazus	Frequent Version Updates	Federal Emergency Management Agency (FEMA)	<u>Hazus</u> <u>Methodology</u>	Community	United States	Earthquake, Flood, Hurricane, Tsunami	Post	Yes	Yes	Yes
Open Resilience Index (ORI)	2021	Feldmeyer, D; et. al.	An open resilience index: Crowdsourced indicators empirically developed from natural hazard and climatic event data	National	Global	All-hazards	Pre	Yes	Yes	Yes
Japanese Social Capital and Social Vulnerability Indices	2021	Fraser, T	Japanese Social Capital and Social Vulnerability Indices: Measuring Drivers of Community	Local	Japan	All-hazards	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
			Resilience 2000- 2017							
Conceptual Framework for Social Vulnerability	2021	Mason, K; et. al.	Social Vulnerability Indicators for Flooding in Aotearoa New Zealand	Local	New Zealand	Flood	Pre	Yes	Yes	Yes
	2021	Nursey-Bray, et. al.	Developing indicators for adaptive capacity for multiple use coastal regions: Insights from the Spencer Gulf. South Australia	Local	Australia	All-hazards	Pre	Yes	Yes	Yes
Australian Disaster Resilience Index (ADRI)	2021	Parsons, M; et. al.	Disaster resilience in Australia: A geographic assessment using an index of coping and adaptive capacity	National	Australia	All-hazards	Pre	Yes	Yes	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
	2021	Zarghami, SA; Dumrak, J	A system dynamics model for social vulnerability to natural disasters: Disaster risk assessment of an Australian city	Local	Australia	All-hazards	Pre	Yes	No	Yes
Composite Community Disaster Resilience Index (CCDRI)	2020	Al Rifat, SA; Liu, WB	Measuring Community Disaster Resilience in the Conterminous Coastal United States	County	United States	All-hazards	Pre	Yes	Yes	Yes
Regional Climate Resilience Index (RCRI)	2020	Feldmeyer, D; et. al.	Regional Climate Resilience Index: A Novel multimethod Comparative Approach for Indicator Development, Empirical Validation and Implementation	County	Germany	All-hazards	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
	2020	Yang, YF; et. al.	A Federated Pre- Event Community Resilience Approach for Assessing Physical and Social Sub- Systems: an Extreme Rainfall Case In Hong Kong	Urban	Hong Kong	All-hazards	Pre and Post	Yes	Yes	No
	2020	Zobel, CW; Baghersad, M	Analytically comparing disaster resilience across multiple dimensions	Local	United States	All-hazards	Post	Yes	Yes	No
	2019	Gillespie- Marthaler, L; et. al.	Selecting Indicators for Assessing Community Sustainable Resilience	Local	United States	All-hazards	Pre	Mixed	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
DRIFT	2019	Manyena, B; Machingura, F; O'Keefe, P	Disaster Resilience Integrated Framework for Transformation (DRIFT): A new approach to theorizing and operationalizing resilience	Local	Global	All-hazards	Pre	Yes	Yes	No
Comprehensi ve Disaster Resilience Index (CDRI2)	2019	Marzi, S; et. al.	Constructing a Comprehensive Disaster Resilience Index: The case of Italy	Local	Italy	All-hazards	Pre	Yes	Yes	Yes
	2019	Nicholson, D; Vanli, OA; Jung, S; Ozguven, EE	A spatial regression and clustering method for developing place- specific social vulnerability indices using census and social media data	Local	United States	All-hazards	Post	Yes	Yes	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
	2018	Rohith, VR; et. al.	Disaster Preparedness Index: A Valid and Reliable Tool to Comprehend Disaster Preparedness in India	Local	India	All-hazards	Pre	No	Yes	No
5S Social Resilience Framework	2018	Saja, AMA; et. al.	An inclusive and adaptive framework for measuring social resilience to disasters	Local	Global	All-hazards	Pre	No	Yes	No
NaHRSI	2018	Summers, JK; et. al.	Measuring Community Resilience to Natural Hazards: The Natural Hazard Resilience Screening Index (NaHRSI) - Development and Application to the United States	County	United States	All-hazards	Pre	Yes	No	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
ANDRI2	2017	P. Morley et. al.	The Australian Natural Disaster Resilience Index (ANDRI2): A System for Assessing the Resilience of Australian Communities to Natural Hazards	Community	Australia	Natural	Pre	Mixed	Yes	Yes
GRI	2017	FM Global	2018 FM Global Resilience Index (GRI)	Country	Global	Multiple	Pre	Yes	Yes	No
CREAT	2016	U.S. Environment al Protection Agency	Climate Resilience Evaluation and Awareness Tool (CREAT)	Water Utilities	United States	Climate Risk	Pre	Mixed	No	No
	2016	National Institute of Standards and Technology (NIST)	Community Resilience Planning Guide for Building and Infrastructure Systems (Volumes 1 and 2)	Community	Kenya/ Uganda	Infrastructure	Pre	No	Yes	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
RIM	2016	N.S. Lam et al.	Resilience Inference Measurement (RIM): Measuring Community Resilience to Coastal Hazards along the Northern Gulf of Mexico	County	United States	Coastal Hazards	Post	Yes	Yes	Yes
WRI	2016	Institute for Environment and Human Security of the United Natio ns	World Risk Index (WRI)	Country	Global	Multiple	Pre	Yes	Yes	Yes
AGIR	2015	European Commission	Measuring and Monitoring Progress on Resilience Building for Food and Nutrition Security	Country	West Africa	Food Security	Pre	Mixed	No	Yes
CDR	2015	D. Keun et al.	A Measurement of Community Disaster Resilience (CDR) in Korea	Community	South Korea	Natural	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
CDRST	2015	Torrens Resilience Institute	Developing a Model and Tool to Measure Community Disaster Resilience	Community	Australia	Multiple	Pre	Mix	Yes	Mixed
CRDSA	2015	S.A. Alshehri et al.	Disaster Community Resilience Assessment Method: A Consensus based Delphi and AHP Approach	Community	Saudi Arabia	Multiple	Pre	Mix	No	No
CR-E	2015	Nasrullah et al.	Status of Community Resilience in Disaster Prone Districts of Pakistan	District	Pakistan	Earthquake	Pre	Yes	Yes	No
CRF	2015	The Rockefeller Foundation, Arup	City Resilience Framework (CRF) and City Resilience Index	City	Global	Multiple	Pre	No	Yes	No
FSRI	2015	New Economics Foundation	Financial System Resilience Index (FSRI)	Country	Global	Financial System	Pre	Yes	No	No
RELi	2015	Capital Markets Partnership	RELi Resilience Action Checklist	Community	United States	Infrastructure	Pre	No	Yes	No
TCRI	2015	T. Perfrement and T. Lloyd	The Composite Resilience Index (TCRI)	Community	Australia	Natural	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
TNC Coastal Resilience	2015	The Nature Conservancy (TNC)	Coastal Resilience Mapping Tool	Community	Global	Coastal Hazards	Pre	Yes	No	Yes
UDRI	2015	Earthquakes and Megacities Initiative	A Guide to Measuring Urban Risk Resilience – the Urban Disaster Risk Index (UDRI)	City	Global	Natural	Post	Mixed	Yes	No
Spatially Explicit Resilience Vulnerability Model (SERV)	2014	Tim G. Frazier, et. al.	A framework for the development of the SERV model: A Spatially Explicit Resilience-Vulnerability model	Local	United States	Flood	Pre	Yes	No	No
ASPIRE	2014	The World Bank	The Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE)	Country	Global	Poverty	Pre	Yes	Yes	Yes
BRIC	2014	Susan Cutter et al.	Baseline Resilience Indicators for Communities (BRIC), The Geographies of Community Disaster Resilience	County	United States	Multiple	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
CoBRA	2014	United Nations Development Programme (UNDP)/Dryla nds Development Centre	Community Based Resilience Analysis (CoBRA)	Community	Kenya, Uganda	Drought	Pre	No	Yes	No
CRS	2014	Community and Regional Resilience Institute, Meridien	A Practical Approach to Building Resilience: Community Resilience System (CRS)	Community	United States	Multiple	Pre	Yes	No	No
FCR	2014	International Federation of Red Cross (IFRC)	IFRC Framework for Community Resilience (FCR)	Community	Global	Multiple	Pre	Mixed	Yes	No
Grosvenor	2014	Grosvenor	Resilient Cities Research Report	City	Global	Multiple	Pre	Mixed	No	N/A
RCI	2014	Foster, K.A.	Resilience Capacity Index (RCI)	Metro- politan Statistical Area	United States	Multiple	Pre	Yes	Yes	Yes
RRI – Rural	2014	Rural Disaster Resilience Project	Rural Resilience Index (RRI)	Community - Rural	Global	Multiple	Pre	No	No	N/A

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
UCR	2014	Rockefeller Foundation	Urban Climate Resilience (UCR): A Review of Methodologies Adopted under the ACCCRN Initiative in Indian Cities	City	India	Natural	Pre	No	No	No
United Nations International Strategy for Disaster Reduction (UNISDR)	2014	UNISDR	<u>Disaster</u> <u>Resilience</u> <u>Scorecard for</u> <u>Cities</u>	City	Global	Multiple	Pre	No	Yes	No
WISC	2014	Well-being, Identity, Services and Capitals (WISC)	Theorizing Community Resilience to Improve Computational Modeling	Community	United States	Multiple	Pre	Yes	No	Yes
CCRAM	2013	D. Leykin et al.	Conjoint Community Resilience Assessment Measure (CCRAM)	Community	Global	Multiple	Pre and post	Mixed	No	No
CRR	2013	World Economic Forum	Global Risks 2013	Country	Global	Multiple	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
CV	2013	Texas A&M University, Hazard Reduction and Recovery Center	Status and Trends of Coastal Vulnerability (CV) to Natural Hazards Project	County	United States	Coastal Hazards	Pre	Yes	Yes	Yes
IDRI	2013	United Nations Development Programme	Indonesia Disaster Recovery Index (IDRI)	Community	Indonesia	Volcano/ Flood	Post	Mixed	No	Yes
IDS	2013	Institute of Development Studies (IDS)	Towards a Quantifiable Measure of Resilience	Multi-level	Global	Food Security	Pre	Yes	Yes	N/A
LDRI	2013	P.M. Orencio and M. Fujii	Localized Disaster- Resilience Index (LDRI)	Community	Philippines	Coastal Hazards	Pre	Mixed	No	No
ODI	2013	NIST	Overseas Development Institute (ODI). Disaster Risk Management Potential Targets and Indicators	Community	Global	Multiple	Pre and Post	Yes	No	N/A

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
ORP	2013	Oregon Seismic Safety Policy Advisory Commission	The Oregon Resilience Plan (ORP) Reducing Risk and Improving Recovery for the Next Cascadia Earthquake and Tsunami	Regional	Oregon	Infrastructure	Post	Mixed	Yes	No
OXFAM	2013	OXFAM	A Multidimensional Approach to Measuring Resilience	Community	Global	Humanitarian	Pre	Mixed	No	No
RMI	2013	Argonne National Laboratory	Resilience Measurement Index (RMI): Indicator of Critical Infrastructure Resilience	Facility	United States	Infrastructure	Pre	Mixed	No	Mixed
RRI2	2013	DARA	Risk Reduction Index (RRI2)	Territorial Units	West Africa	Multiple	Pre	No	Yes	No
SERI	2013	Verisk Maplecroft	Socio-economic Risk Index (SERI)	Country	Global	Multiple	Pre	Yes	No	N/A
Surging Seas	2013	Climate Central	Surging Seas Risk Finder	Community	U.S. Coast	Storm Surge/Flood	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
US Agency for International Development (USAID)	2013	Feed the Future	Community Resilience: Conceptual Framework and Measurement – Feed the Future Learning Agenda	Community	Global	Poverty	Pre	Yes	No	No
CART	2012	R.L. Pfefferbaum et al.	<u>Communities</u> <u>Advancing</u> <u>Resilience Toolkit</u> (CART)	Community	United States	Multiple	Pre	No	Yes	No
DRLA	2012	Disaster Resilience Leadership Academy (DRLA), Tulane University	Haiti Humanitarian Assistance Evaluation: Resilience Perspective	Household	Haiti	Natural	Pre	Mixed	Yes	No
GFM	2012	UN Office for the Coordination of Humanitaria n Affairs (OCHA) and Maplecroft	Global Focus Model (GFM)	Country	Global	Multiple	Pre	Yes	No	Mixed
ICBRR	2012	Canadian Red Cross	Measuring Disaster-Resilient Communities; Integrated Community Based Risk Reduction (ICBRR)	Coastal Community	Indonesia	Coastal Hazards	Pre	Mixed	No	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
LCOT	2012	Tufts University	<u>Livelihoods</u> <u>Change Over Time</u> (LCOT)	Household	Sudan, Ethiopia, Haiti	Multiple	Post	Yes	Yes	Yes
BCRD	2011	RAND	Building Community Resilience to Disasters (BCRD)— A Way Forward to Enhance National Health Security	Community	United States	Health	Pre	Mixed	No	Mixed
PVI	2011	Inter- American Development Bank	Indicators of Disaster Risk and Risk Management; Prevalent Vulnerability Index (PVI)	Country and Sub- national	Latin America	Multiple	Pre	Yes	No	Yes
ResilUS	2011	U.S. Resilience Institute, Western Washington University	U.S. Resilience Institute (<u>ResilUS)</u>	Community	United States	Earthquake	Post	Yes	No	Yes
SVI	2011	Agency for Toxic Substances & Disease Registry	Social Vulnerability Index (SVI)	County	United States	Multiple	Pre	Yes	Yes	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
Community Disaster Resilience Index (CDRI)	2010	W. G. Peacock, et. al.	Advancing Resilience of Coastal Localities: Developing. Implementing and Sustaining the Use of Coastal Resilience Indicators	Coastal	U.S. Coastal	Multiple	Pre	Mixed	Yes	Yes
CDRI3	2010	Kyoto University, UNISDR	Climate and Disaster Resilience Initiative (CDRI3); Capacity Building Program	City	Southeast Asia	Multiple	Pre	Mixed	Yes	No
CERI	2010	Advantage West Midlands	Community Economic Resilience Index (CERI)	Community	U.K.	Recession	Pre	Yes	Yes	Yes
CRI	2010	Mississippi- Alabama Sea Grant Consortium	Coastal Resilience Index (CRI): A Community Self- Assessment	Community	United States – Coastal	Coastal Hazards	Post	No	Yes	No
CRI2	2010	K. Sherrieb et al.	Measuring Capacities for Community Resilience, Community Resilience Index (CRI2)	County	United States	Multiple	Pre	Yes	No	Yes

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
DROP	2010	S. Cutter et al.	Disaster Resilience of Place (DROP). Disaster Resilience Indicators for Benchmarking Baseline Conditions	County	United States - Southeast	None	Pre	Yes	Yes	Yes
FAO	2010	Food and Agriculture Organization (FAO) of the United Nations (UN)	FAO Resilience Tool	Community	Global	Food Security	Pre	Yes	Yes	Yes
FAO- Livelihoods	2010	L. Alinovi et al., European Report on Development	Livelihoods Strategy and Household Resilience to Food Insecurity	Country	Kenya	Food Security	Pre	Yes	Yes	No
PEOPLES	2010	NIST, MCEER: University of Buffalo	PEOPLES Resilience Framework	Community	United States	Multiple	Pre	Mixed	No	Yes
CRT	2009	Bay Localize	Community Resilience Toolkit (CRT): Workshop Guide	City or County	United States	Climate Change	Pre	No	Yes	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
DFID	2009	DFID Disaster Risk Reduction Interagency Coordination Group	Characteristics of a Disaster- Resilient Community	Community	Global	Multiple	Pre	Mixed	Yes	No
SPUR	2009	San Francisco Planning + Urban Research Association (SPUR)	The Resilient City: Defining What San Francisco Needs from its Seismic Mitigation Policies	Community	United States	Earthquake/ Infrastructure	Post	Yes	No	No
CARRI	2008	Oak Ridge National Laboratory	Community and Regional Resilience Initiative (CARRI)	Community	United States	Multiple	Pre	Yes	Yes	Not Identifie d
Hyogo	2008	International Strategy for Disaster Reduction	Indicators of Progress: Guidance on Measuring the Reduction of Disaster Risks and the Implementation of the Hyogo Framework for Action	City	Global	Natural	Pre and Post	Mixed	Yes	No

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
RASA	2008	B. Maguire and S. Cartwright	Assessing a Community's Capacity to Manage Change: A Resilience Approach to Social Assessment (RASA)	Community	Australia (rural)	Water Scarcity	Pre	No	Yes	No
Resilient Capacity Index (RCI2) - Regions	2008	Berkeley Institute of Urban and Regional Development	Resilience and Regions: Building Understanding of the Metaphor	Metro Regions	Global	Multiple	Pre	N/A	Yes	N/A
CCR/ IOTWS	2007	USAID-Asia Community Coastal Resilience (CCR)	A Guide for Evaluating Coastal Community Resilience to Tsunami/Other Hazards	Community	Southeast Asia	Tsunami	Pre	No	Yes	No
MCEER R4	2007	Multidisciplin ary Center for Earthquake Engineering Research (MCEER), University of Buffalo	Conceptualizing and Measuring Resilience	Community	Global	Infrastructure	Pre	N/A	Yes	N/A

Name	Date Published	Author/ Developer	Title	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Disaster	Quant- itative?	Public Domain?	Public Data Source?
TRIAMS	2006	World Health Organization	Isunami Recovery Impact Assessment and Monitoring System Risk Reduction Indicators (TRIAMS)	Community	Indian Ocean	Tsunami	Post	Mixed	Yes	No
THRIVE	2004	Prevention Institute	Tool for Health & Resilience in Vulnerable Environments (THRIVE)	Community	United States	Health Disparity	Pre	Mixed	Yes	No
Social Vulnerability Index (SoVI)	2003	Cutter, SL; Boruff, BJ; Shirley, WL	Social Vulnerability to Environmental Hazards	County	United States	All-hazards	Pre	Yes	Yes	Yes

Appendix B: List of 2022 Community Resilience Indicator Analysis (CRIA) Methodologies

- * Indicates a methodology in the 2018 CRIA
- ^ Indicates an international methodology

Australian Natural Disaster Resilience Index (ANDRI2)*^

Phil Morley, Melissa Parsons and Sarb Johal, 2017, "The Australian Natural Disaster Resilience Index: A System for Assessing the Resilience of Australian Communities to Natural Hazards," Bushfire & Natural Hazards CRC. Available at https://www.bnhcrc.com.au/research/hazard-resilience/251, accessed March 27, 2018.

Baseline Resilience Indicators for Communities (BRIC)*

Susan L. Cutter, Kevin D. Ash and Christopher T. Emrich, 2014, "Baseline Resilience Indicators for Communities, the Geographies of Community Disaster Resilience," *Global Environmental Change* 29, 65–77. Available at

https://www.sciencedirect.com/science/article/pii/S0959378014001459?casa_token=30407z10 Qm0AAAAA:Y5ulORVy-s9vrNcwASxOb28AD15MgS35Urfa1VCQ1n7Hae3Mt3oR6y-Kjes9Y7K_f1HQiOYB, accessed January 24, 2022.

Composite Community Disaster Resilience Index (CCDRI)

Rifat, S. A. A., & Liu, W., 2020, "Measuring Community Disaster Resilience in the Conterminous Coastal United States." *ISPRS International Journal of Geo-Information*. Available at https://www.mdpi.com/2220-9964/9/8/469/pdf accessed November 19, 2021.

Community Disaster Resilience Index (CDRI)*

Walter Gillis Peacock, et al., 2010, "Advancing Resilience of Coastal Localities: Developing, Implementing, and Sustaining the Use of Coastal Resilience Indicators: A Final Report," *Hazard Reduction and Recovery Center*, December. Available at

https://www.researchgate.net/profile/Walter Peacock/publication/254862206 Final Report Advancing the Resilience of Coastal Localities 10-02R/links/00b7d51feb3e3d0d4a000000.pdf. accessed April 6, 2018.

Comprehensive Disaster Resilience Index (CDRI2)^

Marzi, S., Mysiak, J., Essenfelder, A. H., Amadio, M., Giove, S., & Fekete, A., 2019, "Constructing a Comprehensive Disaster Resilience Index: The Case of Italy." *PloS one*. Available at https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0221585, accessed November 19, 2021.

Community Resilience Index (CRI2)*

Kathleen Sherrieb, Fran H. Norris and Sandro Galea, 2010, "Measuring Capacities for Community Resilience," Social Indicators Research 99: 227–247. Available at

https://link.springer.com/article/10.1007/s11205-010-9576-9, accessed January 24, 2022.

Disaster Resilience of Place (DROP)*

Susan L. Cutter, Christopher G. Burton and Christopher T. Emrich, 2010, "Disaster Resilience of Place, Disaster Resilience Indicators for Benchmarking Baseline Conditions," *Journal of Homeland Security and Emergency Management* 7. Available at

https://www.degruyter.com/abstract/j/jhsem.2010.7.1/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732/jhsem.2010.7.1

Fraser[^]

Fraser, T., 2021, "Japanese Social Capital and Social Vulnerability Indices: Measuring Drivers of Community Resilience 2000–2017." *International Journal of Disaster Risk Reduction*. Available at https://www.sciencedirect.com/science/article/pii/S2212420920314679?casa_token=oaC86lYRuwgAAAAA:ChyrqLcLG-4TT_ZqxEMMDP9oFyRMJODxQ6To9x5yfaLmZxYOMUb4qc3Ulx1UdteBCftuEd7d, accessed November 19, 2021.

Nursey-Bray^

Nursey-Bray, M., Gillanders, B., & Maher, J. A., 2021, "Developing Indicators for Adaptive Capacity for Multiple Use Coastal Regions: Insights from the Spencer Gulf, South Australia." *Ocean & Coastal Management*. Available at

https://www.sciencedirect.com/science/article/pii/S0964569121002118?casa_token=ofxgFiTUUE_ OAAAAA:qsHc0N1BtTDGNR4w5Phl6g9B_QGfpCj1y-GaF1CottH2i3eLEsQzPKLGC40C39LABoed8qmK, accessed November 19, 2021.

Resilience Capacity Index (RCI)*

Kathryn A. Foster, 2014, "Resilience Capacity Index: Disaster Resilience Measurements: Stocktaking of Ongoing Efforts in Developing Systems for Measuring Resilience, *United Nations Development Programme*, February, p. 38. Available at

https://www.preventionweb.net/files/37916 disasterresiliencemeasurementsundpt.pdf, accessed September 11, 2019.

Regional Climate Resilience Index (RCRI)[^]

Feldmeyer, D., Wilden, D., Jamshed, A., & Birkmann, J., 2020, "Regional Climate Resilience Index: A Novel Multimethod Comparative Approach for Indicator Development, Empirical Validation and Implementation." *Ecological indicators*. Available at

https://www.sciencedirect.com/science/article/pii/S1470160X20307998?casa_token=_VRVTAEaj_gUAAAAA:pTCrOFbuAU7Y7mjURGNV44_JYPRbhjy2cqxNXdiDcGhwt6SE-IUfzKFQQopJ0pKyZ2wwwTYB, accessed November 19, 2021.

Social Vulnerability Index (SoVI)

Cutter, Susan L., Bryan J. Boruff and W. Lynn Shirley, 2003, "Social Vulnerability to Environmental Hazards." Social Science Quarterly 84.2. Available at

https://onlinelibrary.wiley.com/doi/pdfdirect/10.1111/1540-

6237.8402002?casa_token=IUAXvoqNhUUAAAAA:SAFjsqpLlMmcdZHyB0n4s6DyUlw65VVv0u9XKwX 4nRakED59dUgGHEW5FKDXDDRjiSTKlvmNzhM1lw, accessed January 18, 2022.

Social Vulnerability Index (SVI)*

Barry E. Flanagan, et al., 2011, "A Social Vulnerability Index for Disaster Management," *Journal of Homeland Security and Emergency Management* 8. Available at

https://svi.cdc.gov/Documents/Data/A%20Social%20Vulnerability%20Index%20for%20Disaster%2 OManagement.pdf, accessed April 6, 2018.

The Composite Resilience Index (TCRI)*

T. Perfrement and T. Lloyd, 2015, "The Composite Resilience Index: The Modelling Tool to Measure and Improve Community Resilience to Natural Hazards," *The Resilience Index*. Available at https://theresilienceindex.weebly.com/our-solution.html, accessed April 6, 2018.

Appendix C: List of 2022 Community Resilience Indicator Analysis (CRIA) Indicators

This appendix provides details about each of the 22 indicators identified through the 2022 CRIA analysis process. For each indicator, the tables below include:

- Indicator metric;
- Data source;
- National average;
- Binning method used;
- Data geography (available at county, census tract, tribal, Puerto Rico and other);
- Methodologies using this indicator; and
- Author rationale for including this indicator.

Each table notes which of the following methodologies used each indicator:

- Australian Disaster Resilience Index (ANDRI);
- Baseline Resilience Indicators for Communities (BRIC);
- Composite Community Disaster Resilience Index (CCDRI);
- Community Disaster Resilience Index (CDRI);
- Comprehensive Disaster Resilience Index (CDRI2);
- Disaster Resilience of Place (DROP);
- North American Industry Classification System (NAICS);
- U.S. Census Estimates of the Components of Population Change (PEPTCOMP);
- Resilience Capacity Index (RCI);
- Regional Climate Resilience Index (RCRI);
- Social Vulnerability Index (SoVI);
- Social Vulnerability Index (SVI); and
- The Composite Resilience Index (TCRI).

Population Characteristics: 3 Indicators

Population without High School Diploma											
Metric	Data Source										
Percentage of population over age 25 without a high school diploma or General Educational Development (GED)	American Community Survey (ACS) 2016-2020 five-year estimates, Table S1501										
National Average	Binning Methods										
11.5% of the population over age 25 do not have a high school diploma or GED.	Census Tract: Jenks County: Jenks Caspa Caspall										

Data Geography

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
11	Х	Х	Х	Х	Х	Χ	Χ	Χ		Х			Х	Х

Author Rationale for Including This Indicator

Higher levels of education are associated with health, as well as an improved ability to communicate and comprehend information.^{b,g}

Education is included as an input to economic resilience as higher levels of education is a characteristic of a strong labor force and supports individuals' ability to access community resources.c,f

Higher levels of education can improve the capacity to prepare for, and respond to, the stress of disasters. a,e,h

For individuals with lower levels of education, the practical and bureaucratic hurdles to assist in coping with, and recovering from, a disaster are much more difficult to navigate.g

Population Age 65 and Older											
Metric	Data Source										
Percentage of the population age 65 and older	ACS 2016-2020 five-year estimates, Table S0101										
National Average	Binning Methods										
16.0% of the U.S. population is age 65 and older.	Census Tract: Fisher Jenks	County: Jenks Caspall									

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
9	Х	Х			Х		Х	Х	Х			Χ	X	Х

Author Rationale for Including This Indicator

Several methodologies noted that the percentage of elderly adults in the population could affect resilience. a,b,e

Those over 65 tend to be less mobile.h

Those over 65 may find it more difficult to prepare for disasters and to adapt to extreme circumstances.^h

Many people over 65 require assistance from family, neighbors and others, which might not be available during a disaster. $^{\rm g}$

Population with a Disability										
Metric	Data Source									
Percentage of the population with a disability ⁵	ACS 2016-2020 five-year estimates, Table S1810									
National Average	Binning Methods									
12.7% of the U.S. population has a disability	Census Tract: Fisher Jenks	County: Jenks Caspall								

Data is available at the Census tract, county and Tribal level. Puerto Rico is included.

Methodologies Using This Indicator

# 0 1	f	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
7	7	Х	Х			Х	Χ		Χ	Х	Χ				

Author Rational for Including This Indicator

Individuals with disabilities tend to be more vulnerable to physical, social and economic challenges.b,f

Having functional, mobility, or access needs can make responding to disasters more challenging, including adapting to extreme circumstances and dealing with the increased stress. a,f,h

During an emergency, family members, neighbors, or a caretaker may be less able to provide support to individuals with special needs that require the assistance of others.g

Per the ACS question wording, this definition would include individuals with the following conditions: serious difficulty hearing, seeing, walking and/or dressing; serious difficulty because of a physical, mental or emotional condition; serious difficulty concentrating, remembering, making decisions, or doing errands alone.

Household Characteristics: 4 Indicators

Households Without a Vehicle										
Metric	Data Source									
Percentage of occupied housing units with no vehicles available	ACS 2016-2020 five-year estimates, Table B08201									
National Average	Binning Methods									
8.5% of households are without a vehicle.	Census Tract: Jenks Caspall	County: Head Tail Breaks								

Data Geography

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
9	Х	Х	Х		Х		Х	Х	Х		Х			Х

Author Rationale for Including This Indicator

Access to transportation helps individuals support their livelihoods and provides critical mobility to adapt to the extreme circumstances of a disaster.c,e,h

Communities where fewer individuals have access to a vehicle may have less resilience to a disaster.b

Lack of access to vehicle can be especially problematic in terms of evacuation in urban areas where automobile ownership is lower, especially among inner city poor populations.g

Households with Limited English										
Metric	Data Source									
Percentage of households in which everyone 14 and older has difficulty speaking English. ⁶	ACS 2016–2020 five-year estimates, Table S1602									
National Average	Binning Methods									
4.3% of U.S. households are limited English- speaking households where all members 14 or older have difficulty speaking English.	Census Tract: Fisher Jenks	County: Jenks Caspall								

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
7	Х	Х	Χ		Х		Χ	Х	Χ					

Author Rationale for Including This Indicator

Proficiency in English supports community resilience because of improved ability to communicate between individuals, as well as allowing individuals to better access community resources.^{a,c,g}

Greater numbers of proficient English speakers can be vital for effective communication interactions in the event of a disaster.^{b,h}

In communities where the first language is neither English nor Spanish, accurate translations of advisories may be scarce.g

Communities with fewer English-speaking residents may demonstrate lower levels of resilience.e

⁶ A "limited English-speaking household" is one in which no member 14 years and older speaks only English or speaks a non-English language and speaks English "very well." In other words, all members 14 years and older have at least some difficulty with English (https://census.gov/library/visualizations/2017/comm/english-speaking.html.html, accessed August 7, 2018).

Single-Parent Households											
Metric	Data Source										
Percentage of households with single parents of children under 18 (no spouse/partner present)	ACS 2016–2020 five-year estimates, Table B09005										
National Average	Binning Method										
25% of U.S. family households are single parent households.	Census Tract: Jenks County: Jenks Casp										

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
7	Х			Х			Х	Χ		Х			Х	Х

Author Rationale for Including This Indicator

Single-parent households are more vulnerable to a disaster because they tend to have lower socioeconomic status and fewer sources of social support than that of two-parent families.^{d,g}

Single-parent households are also vulnerable as all daily responsibilities fall to one parent, making recovery more difficult.g

Households without a Smartphone										
Metric	Data Source									
Percent of households without a smartphone	ACS 2016–2020 5-year estimates, Table S2801									
National Average	Binning Method									
16.3% of U.S. households do not have a smartphone.	Census Tract: Jenks Caspall	County: Jenks Caspall								

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
5	Χ	Х	Х		Х						Х			

Author Rationale for Including This Indicator

Access to telephones enables communication which is vital during disaster events.b

Communities with more access to telephone services will be better prepared for and will respond better before and during a disaster.

Availability and accessibility of natural hazard information and community engagement encourages risk awareness.^a

Housing: 2 Indicators

Mobile Homes as A Percentage of Housing Units										
Measure	Data Source									
Percentage of housing units that are mobile homes	U.S. Census American Community Survey (ACS) 2016–2020 five-year estimates, Table DP04									
National Average	Binning Methods									
6% of housing units in the U.S. are mobile homes.	Census Tract: Fisher Jenks	County: Fisher Jenks								

Data Geography

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6	Х	Х			Х		Χ	Х			Х			

Author Rationale for Including This Indicator

Higher numbers of mobile homes in a community are related to lower levels of resilience because of the lower-quality construction of these homes and lack of basements, which makes them particularly susceptible to damage from hazards.^{b,e,g}

Mobile homes are frequently found outside of metropolitan areas that may not be readily accessible by interstate highways or public transportation. $^{\rm g}$

Owner-Occupied Housing										
Metric	Data Source									
Percentage of housing units that are owner- occupied	ACS 2016-2020 five-year estimates, Table DP04									
National Average	Binning Methods									
64.4% of housing units in the U.S. are owner-occupied.	Census Tract: Jenks County: Fisher Je									

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6	Х	Х	Х		Х	Χ			Х					

Author Rationale for Including This Indicator

Home ownership is often included as a measure of a community's economic strength and thus is a marker of community resilience.b,c,e,h

Home ownership is also used to reflect residents' levels of place attachment to their communities.c,f

Low levels of home ownership can indicate a community with a faltering economy and a population with less long-term commitment to the community, which could hamper both individual and community mitigation actions to prepare for disaster as well as recovery efforts.^{a,f}

Healthcare: 3 Indicators

Number of Hospitals										
Metric	Data Source									
The number of hospitals per 10,000 people	U.S. Census Bureau, 2020 County Business Patterns, Table 00A1, NAICS code 622110									
National Average	Binning Method									
There are .2 hospitals per 10,000 people in the U.S.	Census Tract: Fisher Jenks	County: Head Tail Breaks								

Data Geography

Data is available at the county level. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
9	Х	Х	Х		Х		Х		Х		Х	X		X

Author Rationale for Including This Indicator

This measure represents essential community infrastructure, both because it represents the capacity of the healthcare system to support residents' overall health and to provide critical emergency medical care. a,b,c,e,h

Lack of this critical capacity negatively affects a community's ability to respond to and recover from disasters.c

Medical Professional Capacity						
Metric	Data Source					
The number of health-diagnosing and treating practitioners per 1,000 population	ACS 2016-2020 five-yes S2401	ar estimates, Table				
National Average	Binning Methods					
There are 19.9 health diagnosing and treating practitioners per 1,000 population in the U.S.	Census Tract: Jenks Caspall County: Fisher Jenk					

Data is available at the county level. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
8	Х	Х	Х	Х	Х						Х	Χ		Χ

Author Rationale for Including This Indicator

Availability of physicians is linked with the overall physical and mental health of community residents. b,c,d,e

Lack of access to physicians is related to lower levels of overall community resilience as indicated by low birthweight and premature mortality.d

Physicians are a critical emergency resource in the response to and recovery from a disaster.^a

Population without Health Insurance										
Metric	Data Source									
Percentage of the population without health insurance	ACS 2016-2020 5-year estimates, Table S2701									
National Average	Binning Methods									
8.7% of the U.S. population does not have health insurance.	Census Tract: Jenks County: Fisher Je									

Data is available at the Census tract, county and tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
7		Х	Х		Х	Χ	Х				Х			Х

Author Rationale for Including This Indicator

Health is a critical component of community well-being. An unhealthy population has more difficulty accessing community support or engaging in the process of building disaster resilience.c.e

Communities with more individuals covered by health insurance tend to have higher measures of physical and mental health.b,e

Health insurance coverage is one indication of individuals' capacity to effectively respond to and recover from a crisis, both mentally and physically.^f

Communities with lower percentages of individuals with health insurance may have lower levels of resilience.e

Economic: 6 Indicators

Unemployed Labor Force	Unemployed Labor Force											
Metric	Data Source											
Percentage of the civilian labor force age 16 and over who are unemployed	ACS 2016-2020 five-year estimates, Table DP03											
National Average	Binning Methods											
5.4% of the civilian labor force age 16 and over are unemployed.	Census Tract: Jenks Caspall	County: Fisher Jenks										

Data Geography

Data is available at the Census tract, county and tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
13	Х	Х	Х	Х	Х		Х	Х	Х	Х	Х	Х	Х	Х

Author Rationale for Including This Indicator

High levels of employment contribute to a healthy community economy, which supports community resilience. a,b,d,e,h

Employment also provides residents with financial resources that contribute to their livelihoods.c

Unemployed persons do not have the employee benefit plans that provide income and health cost assistance in the event of injury or death.g

Counties with higher levels of unemployment may have fewer community resources to support residents' needs and a population that is both less prepared for a disaster and less able to cope with the aftermath.^h

Income Inequality										
Metric	Data Source									
Gini Index of income distribution across a population; the closer to 1, the greater the income inequality. ⁷	ACS 2016-2020 five-year estimates, Table B19083									
National Average	Binning Method									
The average Gini Index in the U.S. is .48.	Census Tract: Jenks Caspall	County: Fisher Jenks								

Data is available at the county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
10		Х		Х	Х	Χ					Х		Х	

Author Rationale for Including This Indicator

The economic environment is a major factor in a community's resilience; and when income inequality is present, earnings tend to be distributed in a way that does not support broader community goals.^{b,d,e}

A skewed distribution of economic resources may negatively affect the cohesiveness of the residents' response to a disaster.^f

⁷ The Gini Index or coefficient uses a scale of 0–1 to measure the difference between the ideal distribution of income (perfect equality [0] where 50 percent of the population would receive 50 percent of the available income) and the actual distribution. The closer the number is to 1, the greater the income inequality.

Median Household Income	Median Household Income											
Metric	Data Source											
Median household income	ACS 2016-2020 five-year estimates, Table S1903											
National Average	Binning Methods											
The median household income in the U.S. is \$64,994.	Census Tract: Manual	County: Manual										

Data is available at the Census tract, county and tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6	Х		Х	Х					Χ	Χ			Х	

Author Rationale for Including This Indicator

There is a strong relationship between individuals' financial resources and their resilience to a disaster. b,c

Low-income households are at greater risk because they tend to live in lower-quality housing situated in higher risk areas, are less likely to have prepared for a disaster and have fewer resources to support recovery.c

The median household income of a community may also reflect its economic resilience and the community resources available to support recovery.^h

Unemployed Women in the Labor Force											
Metric	Data Source										
Percent of women in the civilian work force age 16 and over who are unemployed	ACS 2016-2020 5-year estimates, Table DP03										
National Average	Binning Method										
5.5% of women in the workforce age 16 and over are unemployed.	Census Tract: Jenks Caspall	County: Fisher Jenks									

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6		Х			Х		Χ			Χ			Х	Χ

Author Rationale for Including This Indicator

Communities enhance disaster resilience through nondiscriminatory wage policies, ensuring that all groups have fair access to resources.^b

Economic stability at the community level, particularly the stability of livelihoods is an indicator of resilience.

Population Below Poverty Level											
Metric	Data Source										
Population below U.S. Census poverty level in past 12 months ⁸	ACS 2016-2020 5-year estimates, Table S1701										
National Average	Binning Method										
12.8% of the U.S. population lives below the poverty level.	Census Tract: Jenks Caspall County: Jenks Caspall										

Data is available at the Census tract, county and Tribal levels. Puerto Rico is included.

Methodologies Using This Methodology

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
5	Х					Χ	Χ	Х					Х	

Author Rationale for Including This Indicator

Economic resources play an important role in boosting resilience and adaptive capacity.

Economically disadvantaged populations are disproportionately affected by disasters. The poor are less likely to have the income or assets needed to prepare for a possible disaster or to recover after a disaster.g

 $^{{}^{8}\} For\ more\ on\ how\ the\ Census\ defines\ poverty\ see:}\ \underline{https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html}.$

Workforce Employed in Predominant Sector											
Metric	Data Source										
Percent of workforce employed in the predominant sector	ACS 2016-2020 5-year estimates, Table DP03										
National Average	Binning Method										
24.7% of the workforce is employed in the dominant sector of their county.	Census Tract: Fisher Jenks County: Fisher Jen										

Data is available at the Census tract, county and tribal levels. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
5	Х	Х		Х	Χ	Х								

Author Rationale for Including This Indicator

Diversity is important for long term economic resilience; the local economy should not be overly dependent on continuing success in just one sector.^b

In a diversified environment, if one industry weakens or fails, there are others that can provide employment and sustain the regional economy.^d

Connection to Community: 4 Indicators

Percent of Inactive Voters							
Metric	Data Source						
Percent of inactive voters (defined differently by state) 9	2020 U.S. Election Assistance Commission - Election Administration and Voting Survey						
National Average	Binning Method						
9.0% of registered voters in the U.S. are inactive. 10	Census Tract: Fisher Jenks	County: Fisher Jenks					

Data Geography

Data is available at the county level. Alaska, Puerto Rico and territorial data were provided at a State/Territorial level only so the data for counties within those areas were imputed from the State/Territorial number. ¹¹

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
10	Х	Х	Х	Х	Х	Χ					Х	Χ	Х	Х

Author Rationale for Including This Indicator

An active voting population is an indicator of having a community that is engaged, enhancing overall community resilience.

Participation in elections increases social and political trust.

Civic engagement, including voting, is an important form of bridging social capital.k

⁹ Inactive voter is defined by each State. For more information see:

https://www.eac.gov/sites/default/files/eac_assets/1/1/2014_Statutory_Overview_Final-2015-03-09.pdf.

10 For more information on the Election Administration and Voting Survey 2020 Comprehensive Report see: https://www.eac.gov/sites/default/files/document_library/files/2020_EAVS_Report_Final_508c.pdf.

11 For more information on the Election Administration and Voting Survey 2020 Comprehensive Report see: https://www.eac.gov/sites/default/files/document_library/files/2020_EAVS_Report_Final_508c.pdf.

Presence of Civic and Social Organization	ns	
Metric	Data Source	
Number of civic and social organizations per 10,000 people	U.S. Census Bureau, 202 Patterns, Table 00A1, N	•
National Average	Binning Method	
There are .8 civic and social organizations per 10,000 people	Census Tract: Jenks Caspall	County: Head Tail Breaks

Data is available at the county level. Puerto Rico is included.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6		Χ	Х	Χ	Х	Χ								Х

Author Rationale for Including This Indicator

This measure indicates the level of community engagement by looking at the level of civic infrastructure through which residents support their communities. b,d,e,f

Participation in civic organizations provides a mechanism for residents to invest in and take from their community and also increases networking and trusted relationships.^{c,f}

The availability of formal social networks can be critical during response and recovery to quickly mobilize resources and disseminate information.^{b,c,d}

Residents who participate in local civic organizations can use them for help and provide mutually beneficial cooperation during a crisis.^{b,d}

Data Source					
Association of Statisticians of American Religious Bodies. 2010 U.S. Religion Census. http://www.usreligioncensus.org/index.php					
Binning Method					
Census Tract: Jenks County: Jenks Caspall					
	Association of Statisticia Bodies. 2010 U.S. Religi http://www.usreligionce Binning Method Census Tract: Jenks				

Data is available at the county level.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6		Х	Х	Х	Х						Х			Χ

Author Rationale for Including This Indicator

Affiliation with a religious organization or civic organization can be used as a proxy measure for social connectedness, and how much a community may be able to rely on the good will of other local citizens, leading to reciprocity and mutually beneficial cooperation.^{b,d,e}

Religious adherents can access additional support beyond their family and neighbors. Religious organizations are often organized to actively provide physical and social support to their congregations and communities during times of individual and community crisis.^{b,c,d}

Population Change								
Metric	Data Source							
Net change in population from people moving in or out of the county relative to the U.S. mean.	U.S. Census Bureau, Pop Cumulative Estimate of t Resident Population Cha 2016-2020	the Components of						
National Average	Binning Method							
Not Applicable	Census Tract: Standard Deviation	County: Standard Deviation						

Data is available at the county level.

Methodologies Using This Indicator

# of 14	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SoVI	SVI	TCRI	N-B	CCDRI	RCRI	CDRI2	Fraser
6	Χ	Х		Х		Χ				Х	Х			

Author Rationale for Including This Indicator

Communities where large numbers of residents have lived for extended periods are likely to have strong place attachment, be invested in the well-being of the community before a disaster and willing to respond to revitalize a community after a disaster.^{b,f}

Familiarity can help individuals navigate a community during an acute crisis, as well as know how to access services after the crisis has passed.^f

A rapid influx of new residents may result in lower levels of attachment to the community, less familiarity with local hazards and how to prepare for them and fewer community connections that can provide support during a crisis.^{b,d,f}

A reduction in population will reduce local tax income and community resources to respond to a disaster.^b

Key for Methodologies Cited under "Author Rationale for Including This Indicator"

- ^a ANDRI: Phil Morley, Melissa Parsons and Sarb Johal, 2017, "The Australian Natural Disaster Resilience Index: A System for Assessing the Resilience of Australian Communities to Natural Hazards," *Bushfire & Natural Hazards CRC*. Available at https://www.bnhcrc.com.au/research/hazard-resilience/251, accessed Match 27, 2018.
- b BRIC: Susan L. Cutter, Kevin D. Ash and Christopher T. Emrich, 2014, "Baseline Resilience Indicators for Communities, the Geographies of Community Disaster Resilience," *Global Environmental Change* 29, 65–77.
- ^c CDRI: Walter Gillis Peacock, et al., 2010, "Advancing Resilience of Coastal Localities: Developing, Implementing, and Sustaining the Use of Coastal Resilience Indicators: A Final Report," *Hazard Reduction and Recovery Center*, Available at https://pdfs.semanticscholar.org/ea56/1b67fb9fa11964a32e99c4da14ad32dd39de.pdf, accessed April 6, 2018.
- d CRI2: Kathleen Sherrieb, Fran H. Norris and Sandro Galea, 2010, "Measuring Capacities for Community Resilience," Social Indicators Research 99: 227–247.
- e DROP: Susan L. Cutter, Christopher G. Burton and Christopher T. Emrich, 2010, "Disaster Resilience of Place, Disaster Resilience Indicators for Benchmarking Baseline Conditions," *Journal of Homeland Security and Emergency Management* 7. Available at http://resiliencesystem.com/sites/default/files/Cutter jhsem.2010.7.1.1732.pdf, accessed April 6, 2018.
- f RCl: Kathryn A. Foster, 2014, "Resilience Capacity Index, Disaster Resilience Measurements: Stocktaking of Ongoing Efforts in Developing Systems for Measuring Resilience, *United Nations Development Programme*, 38. Available at https://www.preventionweb.net/files/37916_disasterresiliencemeasurementsundpt.pdf, accessed April 6, 2018.
- g SVI: Barry E. Flanagan, et al., 2011, "A Social Vulnerability Index for Disaster Management," *Journal of Homeland Security and Emergency Management* 8. Available at https://svi.cdc.gov/Documents/Data/A%20Social%20Vulnerability%20Index%20for%20Disaster%20Management.pdf, accessed April 6, 2018.
- ^h TCRI: T. Perfrement and T. Lloyd, 2015, "The Resilience Index: The Modelling Tool to Measure and Improve Community Resilience to Natural Hazards," *The Resilience Index*. Available at https://theresilienceindex.weebly.com/our-solution.html, accessed April 6, 2018.
- ¹ CCDRI: Rifat, S. A. A., & Liu, W., 2020, "Measuring Community Disaster Resilience in the Conterminous Coastal United States." *ISPRS International Journal of Geo-Information*. Available at https://www.mdpi.com/2220-9964/9/8/469/pdf accessed November 19, 2021.
- CDRI2: Marzi, S., Mysiak, J., Essenfelder, A. H., Amadio, M., Giove, S., & Fekete, A.., 2019, "Constructing a Comprehensive Disaster Resilience Index: The Case of Italy." *PloS one*. Available at https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0221585, accessed November 19, 2021.
- k Fraser: Fraser, T., 2021, "Japanese Social Capital and Social Vulnerability Indices: Measuring Drivers of Community Resilience 2000–2017." *International Journal of Disaster Risk Reduction*. Available at <a href="https://www.sciencedirect.com/science/article/pii/S2212420920314679?casa_token=oaC86IYRuwgAAAAA:ChyrqLcLG-4TT_ZqxEMMDP9oFyRMJODxQ6To9x5yfaLmZxYOMUb4qc3UIx1UdteBCftuEd7d, accessed November 19, 2021.
- Nursey-Bray: Nursey-Bray, M., Gillanders, B., & Maher, J. A., 2021, "Developing Indicators for Adaptive Capacity for Multiple Use Coastal Regions: Insights from the Spencer Gulf, South Australia." *Ocean & Coastal Management*. Available at https://www.sciencedirect.com/science/article/pii/S0964569121002118?casa_token=ofxgFiTUUE0AAAAA:qsHc0N1BtTDG NR4w5Phl6g9B QGfpCj1y-GaF1CottH2i3eLEsQzPKLGC40C39LABoed8qmK, accessed November 19, 2021.
- ^m RCRI: Feldmeyer, D., Wilden, D., Jamshed, A., & Birkmann, J., 2020, "Regional Climate Resilience Index: A Novel Multimethod Comparative Approach for Indicator Development, Empirical Validation and Implementation." *Ecological indicators*. Available at https://www.sciencedirect.com/science/article/pii/S1470160X20307998?casa_token=_VRVTAEajgUAAAAA:pTCr0FbuAU7Y7mjURGNV44 JYPRbhjy2cqxNXdiDcGhwt6SE-IUfzKFQQopJ0pKyZ2wwwTYB, accessed November 19, 2021.
- NoVI: Cutter, Susan L., Bryan J. Boruff and W. Lynn Shirley., 2003, "Social Vulnerability to Environmental Hazards." Social Science Quarterly 84.2. Available at https://onlinelibrary.wiley.com/doi/pdfdirect/10.1111/1540-6237.8402002?casa token=IUAXvoqNhUUAAAAA:SAFjsqpLlMmcdZHyB0n4s6DyUlw65VVv0u9XKwX4nRakED59dUq GHEW5FKDXDDRjiSTKIvmNzhM1Iw, accessed January 18, 2022.

Appendix D: 2022 Community Resilience Indicator Analysis (CRIA) Correlation Matrix

The research team conducted a correlation analysis to measure and describe the strength and direction of the relationships among the 22 commonly used community resilience indicators. Correlation analysis shows how individual indicators may be related to each other. Understanding these correlations will help communities design resilience strategies that take these relationships into account.

The Pearson Correlation Coefficient¹² is a numerical measure of linear correlation from −1 to 1.

- A coefficient closer to 1 indicates a positive correlation (variable A increases as variable B increases).
- A coefficient of 0 indicates no correlation.
- A coefficient closer to -1 indicates a negative correlation (variable A increases as variable B decreases).

As jurisdictions consider strategies to address those indicators that reveal challenges to resilience, they should consider relationships between indicators signifying populations that may face multiple challenges. For example, campaigns focusing on individuals that are unemployed should also consider that they are more likely to be single-parent households, have difficulty speaking English, lack a high school diploma and be without access to a vehicle.

Table 2 summarizes some highlights of the correlation analysis.

Table 2: Highlighted Correlation Relationships

Indicator	Positively Correlates With	Negatively Correlates With
Age (adults over 65)	No smartphone (r = 0.45)	Limited English Speaking (r = -0.27)
Low Educational Attainment	Poverty (r = 0.64)No health insurance (r = 0.47)	 Household Income (r = -0.56) Medical Professional Capacity (r = -0.46) (access to healthcare)
Disability	 No smartphone (r = 0.51) Presence of mobile homes (r = 0.46) Poverty (r = 0.45) 	 Household Income (r = -0.64) Medical Professional Capacity (r = -0.31) (access to healthcare)

¹² Stangroom, J. "Pearson Correlation Coefficient Calculator." Social Science Statistics. http://www.socscistatistics.com/tests/pearson/.

Limited English Speaking	Low educational attainment (r = 0.43)	• Age over 65 (r = -0.27)
No Health Insurance	 Low educational attainment (r = 0.47) Limited English speaking (r = 0.35) 	 Medical Professional Capacity (r = -0.38) (access to healthcare) Home Ownership (r= -0.26) Household Income (r= -0.26)
No Vehicle	 Poverty (r = 0.47) Unemployment rate (r = 0.46) Single parent household (r = 0.42) 	 Home ownership (r = -0.33) Household income (r = -0.28) Population change (r = -0.26)
Unemployment Rate	 Unemployed women (r = 0.88) Poverty (r = 0.69) Single parent household (r = 0.51) 	 Household Income (r = -0.44) Home ownership (r = -0.25)
Single-Parent Household	 Poverty (r = 0.62) Unemployment rate (r = 0.51) Income inequality (r = 0.47) Unemployed women (r = 0.47) 	Household Income (r = -0.48)Home Ownership (r = -0.30)
Presence of Mobile Homes	 Low educational attainment (r = 0.43) Disability (r = 0.46) 	 Household income (r = -0.42) Medical professional capacity (r = -0.38) (access to healthcare)
Unemployed Women	Unemployment rate (r = 0.88)Poverty (r = 0.62)	 Household income (r = -0.40) Medical professional capacity (r = -0.22) (access to healthcare)
No Smartphone	 Disability (r = 0.51) Poverty (r = 0.51) Age over 65 (r = 0.45) 	 Household income (r = 0.66) Medical professional capacity (r = -0.30) (access to healthcare)
Poverty	 Low educational attainment (r = 0.64) Unemployment rate (r = 0.69) Single parent household (r = 0.62) Unemployed women (r = 0.62) 	 Household income (r = -0.75) Medical professional capacity (r = -0.33) (access to healthcare)

In <u>Table 3</u> below, the positive correlations have green shading, and the negative correlations have blue. Values that are too small to have statistical significance are marked with an asterisk.

Table 3: Correlation Matrix

	65 and Older	No HS Diploma	With Disability	Limited English	No Health Insurance	No Vehicle	Unemployed	Median Income	Income Inequality	Owner- occupied Housing	Single-Parent Household	Mobile Homes	Medical Professional Capacity	Number of Hospitals	Without Religious Affiliation	Presence of Civic and Social	Population Change	Inactive Voters	Unemployed Women	Workforce in Predominant Sector	No Smartphone	Poverty
65 and Older		-0.13	0.40	-0.27	-0.16	-0.14	-0.08	-0.26	0.02*	-0.12	-0.11	0.12	-0.07	-0.02*	0.01*	0.03*	0.16	-0.07	-0.10	-0.08	0.45	-0.05
No HS Diploma	-0.13		0.40	0.43	0.47	0.31	0.44	-0.56	0.32	-0.21	0.44	0.43	-0.46	-0.04	-0.03*	-0.26	-0.22	0.09	0.42	-0.02*	0.40	0.64
With Disability	0.40	0.40		-0.20	0.07	0.15	0.36	-0.64	0.24	-0.18	0.30	0.46	-0.31	-0.05	0.10	-0.15	-0.02*	0.11	0.31	-0.02*	0.51	0.45
Limited English	-0.27	0.43	-0.20		0.35	0.10	0.04	0.08	0.04	-0.15	0.02*	-0.05	-0.14	0.01*	-0.06	-0.05	-0.10	0.08	0.04	0.03*	-0.16	0.05
No Health Insurance	-0.16	0.47	0.07	0.35		0.10	0.15	-0.26	0.15	-0.26	0.23	0.34	-0.38	-0.04	-0.10	-0.21	-0.05	0.05	0.12	-0.07	0.05	0.23
No Vehicle	-0.14	0.31	0.15	0.10	0.10		0.46	-0.28	0.35	-0.33	0.42	-0.05	-0.09	0.05	0.02*	0.04	-0.26	0.09	0.40	0.16	0.22	0.47
Unemployed	-0.08	0.44	0.36	0.04	0.15	0.46		-0.44	0.37	-0.25	0.51	0.14	-0.24	0.02*	0.14	-0.11	-0.09	0.12	0.88	0.01*	0.25	0.69
Median Income	-0.26	-0.56	-0.64	0.08	-0.26	-0.28	-0.44		-0.39	0.36	-0.48	-0.42	0.41	0.03*	0.05	0.15	0.24	-0.09	-0.40	-0.10	-0.66	-0.75
Income Inequality	0.02*	0.32	0.24	0.04	0.15	0.35	0.37	-0.39		-0.31	0.47	0.14	-0.03*	0.02*	-0.05	-0.10	-0.08	0.07	0.34	0.05	0.21	0.54
Owner- occupied Housing	-0.12	-0.21	-0.18	-0.15	-0.26	-0.33	-0.25	0.36	-0.31		-0.30	-0.10	0.28	0*	-0.01*	0.02*	0.19	-0.13	-0.21	-0.17	-0.19	-0.35
Single-Parent Household	-0.11	0.44	0.30	0.02*	0.23	0.42	0.51	-0.48	0.47	-0.30		0.27	-0.21	0.04	0*	-0.12	-0.19	0.09	0.47	0.01*	0.25	0.62
Mobile Homes	0.12	0.43	0.46	-0.05	0.34	-0.05	0.14	-0.42	0.14	-0.10	0.27		-0.38	-0.06	0.14	-0.22	-0.01*	0.01*	0.13	-0.01*	0.33	0.26
Medical Professional Capacity	-0.07	-0.46	-0.31	-0.14	-0.38	-0.09	-0.24	0.41	-0.03*	0.28	-0.21	-0.38		0.07	-0.02*	0.18	0.12	-0.04	-0.22	0.15	-0.30	-0.33
Number of Hospitals	-0.02*	-0.04	-0.05	0.01*	-0.04	0.05	0.02*	0.03*	0.02*	0*	0.04	-0.06	0.07		0.01*	0.07	-0.02*	0.02*	0.01*	0.04	-0.02*	0*
Without Religious Affiliation	0.01*	-0.03*	0.10	-0.06	-0.10	0.02*	0.14	0.05	-0.05	-0.01*	0*	0.14	-0.02*	0.01*		0.03*	0.25	0.10	0.10	-0.01*	-0.02*	0.01*
Presence of Civic and Social Organizations	0.03*	-0.26	-0.15	-0.05	-0.21	0.04	-0.11	0.15	-0.10	0.02*	-0.12	-0.22	0.18	0.07	0.03*		-0.04	-0.04	-0.12	0.10	-0.07	-0.18
Population Change	0.16	-0.22	-0.02*	-0.10	-0.05	-0.26	-0.09	0.24	-0.08	0.19	-0.19	-0.01*	0.12	-0.02*	0.25	-0.04		-0.07	-0.07	-0.23	-0.25	-0.21
Inactive Voters	-0.07	0.09	0.11	0.08	0.05	0.09	0.12	-0.09	0.07	-0.13	0.09	0.01*	-0.04	0.02*	0.10	-0.04	-0.07		0.10	0.03*	-0.02*	0.11
Unemployed Women	-0.10	0.42	0.31	0.04	0.12	0.40	0.88	-0.40	0.34	-0.21	0.47	0.13	-0.22	0.01*	0.10	-0.12	-0.07	0.10		-0.02*	0.20	0.62
Workforce in Predominant Sector	-0.08	-0.02*	-0.02*	0.03*	-0.07	0.16	0.01*	-0.10	0.05	-0.17	0.01*	-0.01*	0.15	0.04	-0.01*	0.10	-0.23	0.03*	-0.02*		0.10	0.11
No Smartphone	0.45	0.40	0.51	-0.16	0.05	0.22	0.25	-0.66	0.21	-0.19	0.25	0.33	-0.30	-0.02*	-0.02*	-0.07	-0.25	-0.02*	0.20	0.10		0.51
Poverty	-0.05	0.64	0.45	0.05	0.23	0.47	0.69	-0.75	0.54	-0.35	0.62	0.26	-0.33	0*	0.01*	-0.18	-0.21	0.11	0.62	0.11	0.51	

^{*}Not statistically significant

Positive relationships have green shading Negative relationships have blue shading