Community Resilience Indicator Analysis:

County-Level Analysis of Commonly Used Indicators from Peer-Reviewed Research

2020 Update

Homeland Security

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County-Level Analysis of Commonly Used Indicators from Peer-Reviewed Research, 2020 Update

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Argonne National Laboratory's work was supported by the U.S. Department of Homeland Security, Federal Emergency Management Agency, via interagency agreement through U.S. Department of Energy contract DE-AC02-06CH11357. FEMA does not endorse any non-government entities, organizations, or services.

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Executive Summary

> There is no absolute measurement of resilience. This analysis is a relative assessment of resilience, not a scorecard. All areas of the country can improve their readiness as we continue to build a culture of preparedness.

In 2018, the Federal Emergency Management Agency (FEMA) National Integration Center (NIC) Technical Assistance (TA) Branch tasked Argonne National Laboratory (Argonne) with analyzing current community resilience research to provide a data-driven basis to prioritize locations for TA investment and to inform community resilience–related TA content. Argonne's analysis identified 20 commonly used indicators from peer-reviewed research. Fifteen of the 20 indicators use the American Community Survey 5-year average. The original analysis, released in 2018, was based on the ACS 5-year average data for 2012–2016. This paper presents Argonne's analysis methodology, updates the data to the most current ACS census data available ACS 5-year average 2013-2018, and modifies the colors of the chloropleth maps.

To begin the 2018 analysis, the Argonne research team first conducted a literature review to identify meta-analyses of peer-reviewed community resilience assessment methodologies published within the past five years. This search identified six relevant meta-analyses. Next, the research team reviewed the six meta-analyses to catalog each distinct assessment methodology they referenced, ultimately identifying 73 distinct methodologies. Argonne then reviewed these 73 methodologies and retained those that met the following criteria: they used a unit of analysis that corresponded to U.S. county-level data, applied to multiple hazards, had a pre-disaster focus, used quantitative measures, used a publicly available methodology, and used publicly available data sources. Applying these criteria narrowed the pool of methodologies to eight.[1]

The research team then identified more than 100 quantitative indicators used within these eight methodologies and selected only those indicators cited in three or more methodologies. This process resulted in 20 indicators, 11 with a population focus and 9 with a community focus.

This report presents data maps using a "best fit" classification evaluation method to bin the data into five categories. These five bins are shown in Section 1, "Process to Identify and Map Commonly Used Indicators of Community Resilience," under Step 5 as choropleth maps of the United States showing county-level data for each indicator. The analysis of each indicator reveals consistent regional trends across indicators.

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[1] Argonne's examination of community resilience research was extensive and included publications from leading research institutions. Because this field of research is evolving, however, the research cited in this report may not be exhaustive. To avoid bias, Argonne's analysis examined every indicator used in each methodology cited in the meta-analyses and universally applied the selection criteria.

Finally, the research team developed a method to aggregate county-level data from all 20 indicators. Using standard deviations to bin the data, Argonne sorted each U.S. county into five bins and created the "Aggregated Commonly Used Community Resilience Indicator" choropleth map. It is important to note that there is no absolute measurement of resilience. This analysis is a relative assessment of resilience, not a scorecard. All areas of the country can improve their readiness as we continue to build a culture of preparedness.

After binning the aggregated data, 61 counties sorted into the lowest bin and 309 counties sorted into the next lowest bin. These are counties that may face greater challenges to resilience. Many counties in these two bins are in the southeast and southwest parts of the country and in Puerto Rico. Although county-level data can mask more granular issues within a county, this analysis serves as a starting point to prioritize areas of the country to receive TA support from FEMA.

Based on the geographical concentration of counties whose aggregated data falls in the two lowest bins, Argonne identified the following regional areas as potential priority areas for receiving community resilience TA:

- Central Appalachian counties in Kentucky, West Virginia, and Virginia
- The Mississippi Delta region in the states of Louisiana, Mississippi, and Arkansas
- Southwestern Alabama and counties through the Southeast
- Counties and tribal nations in south and central South Dakota
- Counties and tribal nations in New Mexico and Arizona
- South Texas
- Puerto Rico
- The western coast and interior of Alaska.

The analysis of these 20 community resilience indicators, used in multiple peer-reviewed research methodologies, has relevance for many FEMA program areas, as well as for state, local, territorial, and tribal emergency managers and other whole community partners to support initiatives across all phases of emergency management, including mitigation, preparedness, response, and recovery. By reviewing county data for these 20 indicators, emergency managers can gain insights for targeted outreach strategies and for adapting emergency operations plans to community characteristics.

All maps and data can be found on the Resilience Analysis and Planning Tool (RAPT). RAPT data layers include the 20 county-level community resilience indicators identified in the CRIA as well as census-tract level information for 12 of those indicators, infrastructure information drawn from the Homeland Infrastructure Foundation-Level Data (HIFLD) Subcommittee, and hazards, including real-time weather forecasts, historic disasters, and projected hazard risk. RAPT is available at https://bit.ly/ResilienceAnalysisandPlanningTool.

Community Resilience Indicator Analysis:

County-Level Analysis of Commonly Used Indicators from Peer-Reviewed Research, 2020 Update

Introduction

As disasters continue to increase in frequency and cost,[2] researchers across academic disciplines, including anthropology, ecology, engineering, sociology, and psychology, have attempted to identify and quantify features that make a community more resilient to disasters. In 2018, the Federal Emergency Management Agency (FEMA) National Integration Center (NIC) Technical Assistance (TA) Branch asked Argonne National Laboratory (Argonne) to review this body of research to provide a data-driven basis that would assist in prioritizing locations for TA investment and in informing community resilience TA content. The original analysis, released in 2018, was based primarily on U.S. Census and American Community Survey (ACS) 5-year average data for 2012–2016. This paper presents Argonne's analysis methodology, updates census-based indicators with the most recent census and ACS 5-year average data (2014–2018). This report will be updated every three years using future census and ACS 5-year average data as funding allows.

Process to Identify and Map Commonly Used Indicators of Community Resilience

The research team followed a five-step process to identify commonly used indicators from current community resilience research. For the purpose of this study, indicators are quantitative datasets describing the inherent characteristics of a community that contribute to disaster resilience.[3] The team:

1. Conducted a literature review to identify peer-reviewed meta-analyses of different methodologies that measure community resilience to disasters.
2. Cataloged the distinct methodologies cited within the meta-analyses.
3. Created and applied a set of criteria to support the NIC TA Branch's goal of prioritizing locations for TA.

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[2] NOAA (National Oceanic and Atmospheric Administration) National Centers for Environmental Information, 2018, *Billion-Dollar Weather and Climate Disasters: Overview*. Available at https://www.ncdc.noaa.gov/billions/, accessed June 26, 2018. Office of the Director of National Intelligence, 2018, *Statement for the Record: Worldwide Threat Assessment of the US Intelligence Community*. Available at https://www.dni.gov/files/documents/Newsroom/Testimonies/2018-ATA---Unclassified-SSCI.pdf, accessed June 26, 2018.

[3] Susan L. Cutter, Christopher G. Burton, and Christopher T. Emrich, 2010, "Disaster Resilience Indicators for Benchmarking Baseline Conditions," *Journal of Homeland Security and Emergency Management*, 7: Issue 1, Article 51. DOI: 10.2202/1547-7355.1732. Available at https://www.degruyter.com/abstract/j/jhsem.2010.7.1/jhsem.2010.7.1.1732/jhsem.2010.7.1.1732.xml, accessed April 6, 2018.

4. Identified commonly used indicators (i.e., the indicators cited in three or more methodologies) and their associated measures.

5. Grouped county-level data for each indicator into five bins denoting relative resilience and produced choropleth maps.

Step 1: Identify Peer-Reviewed Meta-Analyses

To begin the process of identifying commonly used community resilience indicators, the research team conducted a literature review of electronically available, peer-reviewed meta-analyses from the previous five years that focused on measuring resilience to disasters. Because community resilience research is an emerging field, the five years prior to 2018 constituted a sufficient timeframe and a reasonable boundary condition for embarking on a comprehensive review. To establish a wide-ranging view of the field, the research team included both domestic and international community resilience studies and reviewed each meta-analysis for mentions of additional literature.

The literature review produced the following six meta-analyses:

- Cutter, Susan L., "The Landscape of Disaster Resilience Indicators in the USA," *Natural Hazards* 80 (2015): 741–758. Accessed April 6, 2018; available at https://link.springer.com/article/10.1007%2Fs11069-015-1993-2.
- Koliou, Maria, John W. van de Lindt, Therese P. McAllister, Bruce R. Ellingwood, Maria Dillard, and Harvey Cutler, "State of the Research in Community Resilience: Progress and Challenges," *Sustainable and Resilient Infrastructure* (2017): 1–21. Accessed April 6, 2018; available at http://dx.doi.org/10.1080/23789689.2017.
- Lavelle, Francis M., Liesel A. Ritchie, Alexis Kwasinki, and Brian Wolshon, "Critical Assessment of Existing Methodologies for Measuring or Representing Community Resilience of Social and Physical Systems," *NIST GCR 15-1010* (2015). Accessed April 6, 2018; available at http://dx.doi.org/10.6028/NIST.GCR.15-1010.
- Ostadtaghizadeh, Abbas, Ali Ardalan, Douglas Paton, Jossain Jabbari, and Hamid Reza Khankeh, "Community Disaster Resilience: A Systematic Review on Assessment Models and Tools," *PLoS Currents* (2015). Accessed April 6, 2018; available at http://dx.doi.org/10.1371/currents.dis.f224ef8efbdfcf1d508dd0de4d8210ed.
- Sharifi, Ayyoob, "A Critical Review of Selected Tools for Assessing Community Resilience," *Ecological Indicators* 69 (2016): 629–647. Accessed April 6, 2018; available at http://dx.doi.org/10.1016/j.ecolind.2016.05.023.
- Winderl, Thomas, "Disaster Resilience Measurements: Stocktaking of Ongoing Efforts in Developing Systems for Measuring Resilience," *United Nations Development Programme* (2014). Accessed April 6, 2018; available at https://www.preventionweb.net/files/37916_disasterresiliencemeasurementsundpt.pdf.

The definitions of community resilience used by these methodologies can be found in Appendix A.

Step 2: Catalog Distinct Methodologies, Assessments, and Studies

Reviewing the six meta-analyses, the research team found citations for 72 unique studies, assessments, or methodologies. In addition, although not found in the meta-analysis literature, the following five recently developed methodologies were also reviewed by the research team: The Centers for Disease Control and Prevention's (CDC's) Social Vulnerability Index (SVI) and FEMA's National Risk Index, as well as others currently in development, including the Mitigation Framework Leadership Group's (MitFLG's) Draft Interagency Concept for Community Resilience Indicators and National-Level Measures (published for stakeholder comment), the Alliance for National and Community Resilience's (ANCR's) Community Resilience Benchmarks, and the Johns Hopkins Bloomberg School of Public Health's (JHSPH's) Composite of Post-Event Well-being (COPEWELL). Of these, the research team determined that the CDC's SVI was sufficiently developed to be included in the final list of methodologies, bringing the total to 73.[4]

As additional methodologies are finalized, they can be added to the list for analysis.

Step 3: Create and Apply Inclusion Criteria

The research team established the following inclusion criteria to select the methodologies most relevant to the needs of FEMA NIC TA—a data-driven strategy to prioritize community resilience–related TA delivery. Specifically, the team used the following criteria:

- **County-level unit of analysis.** The team 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 datasets are not available below the county level, and county level is the best for initial national analysis. Methodologies where the unit of analysis was at the level of countries, specific infrastructure assets, or households were excluded.
- **Generalized risk focus.** The NIC provides TA relative to a wide range of hazards, and therefore the inclusion criteria retained methodologies that applied to multiple hazards, eliminating measurement methodologies that focused on one specific risk, such as on earthquakes, food security, poverty, or public health.
- **Pre-disaster focus.** NIC TA supports communities with building resilience prior to a disaster, so the research team included pre-disaster assessments of resilience rather than methods designed to assess how well a community rebounded after a disaster.
- **Quantitative measures.** To ensure that indicators could be easily compared across methodologies, the team included only methodologies that used quantitative measures.
- **Publicly available methodology.** For the analysis and findings to be transparent, the team included only methodologies that were publicly available and excluded any proprietary methodologies.
- **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.

Appendix B, Community Resilience Methodologies, lists all 73 methodologies and includes the meta-analysis sourcing, the date of publication, a link to the methodology report or developer, and a determination for each inclusion criterion.

Through this analysis, the research team identified eight community resilience assessment methodologies that met all of the established inclusion criteria. These eight are the set of community resilience methodologies used for the TA analysis:

- Australian National Disaster Resilience Index (ANDRI)[5]

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[4] CDC's SVI is finalized and all indicators used are publicly available. The National Risk Index incorporates other indices rather than establishing a unique methodology. The methodologies used by the MitFLG, ANCR, and JHSPH are in development, and publicly available information is currently insufficient to include them.

[5] 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)[6]
- Community Disaster Resilience Index (CDRI)[7]
- Community Resilience Index (CRI2)[8]
- Disaster Resilience of Place (DROP)[9]
- Resilient Capacity Index (RCI)[10]
- Social Vulnerability Index (SVI)[11]
- The Composite Resilience Index (TCRI).[12]

Step 4: Identify Commonly Used Indicators

Next, the research team reviewed the set of eight community resilience methodologies and cataloged all of the indicators used in these methodologies, which came to more than 100 unique indicators. The team then identified those indicators that met the inclusion criteria and were found in three or more of the eight methodologies (commonly used indicators). The use of an indicator in three or more methodologies suggests areas where researchers have coalesced on an indicator's importance relative to resilience. This process identified 20 indicators: 11 that are population focused and 9 that are community focused.

Population-focused measures describe attributes that influence an individual's ability to cope with disasters (e.g., age, income, employment). Community-focused measures are qualities inherent to the local community environment that enhance or detract from the community's ability to prepare for, respond to, or recover from a disaster (e.g., the presence of civic associations, hospitals, mobile homes).

While several methodologies grouped indicators or measures into subindexes, or domains, the domains used and the composition of the domains were inconsistent. For example, CRI2 grouped measures into four community capacities (economic development, social capital, information and communication, and community competence), whereas BRIC grouped measures into six community capitals (social, economic, community, institutional, housing/infrastructure, and environmental). Therefore, the Argonne team did not examine domains in this analysis and instead analyzed the individual indicators.

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6 Susan L. Cutter, Kevin D. Ash, and Christopher T. Emrich, 2014, "The Geographies of Community Disaster Resilience," *Global Environmental Change* 29, 65–77.

7 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.

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

9 Susan L. Cutter, Christopher G. Burton, and Christopher T. Emrich, 2010, "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.xml, accessed April 6, 2018.

10 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.

11 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.

12 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*.

Table 1 lists the Commonly Used Community Resilience Indicators identified through this analysis. Indicators are grouped as population focused and community focused, in descending order of the number of citations in the methodologies (highest to lowest).

Table 1. Commonly Used Community Resilience Indicators

Population-Focused Indicators (11)	Number of Methodologies in Which the Indicator Is Used
Educational Attainment (lack of HS diploma)	7
Unemployment Rate	7
Disability	6
English Language Proficiency	6
Home Ownership	6
Mobility (lack of vehicle)	6
Age	5
Household Income	5
Income Inequality	4
Health Insurance	4
Single-Parent Households	3
Community-Focused Indicators (9)	**Number of Methodologies in Which the Indicator Is Used**
Connection to Civic and Social Organizations	6
Hospital Capacity	5
Medical Professional Capacity	5
Affiliation with a Religion	4
Presence of Mobile Homes	4
Public School Capacity	4
Population Change	4
Hotel/Motel Capacity	3
Rental Property Capacity	3

Appendix C includes additional information on each indicator: its metric, data source, which of the eight community resilience methodologies used the indicator, and citations from the methodologies to explain the indicator's connection to resilience. This report includes the most current census data available for the American Community Survey 5-year average (2013–2017).

Step 5: Group County-Level Data for Each Indicator into Five Bins Denoting Relative Resilience and Produce Choropleth Maps

To map the data for each indicator, the research team 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 potential binning methods.[13]

Many classification methods group the data into bins based on mathematically determined "breaks" in the data. Instead of making arbitrary cuts in the data, these methods allowed the research team to group counties that are close in value to each other and maximize the variance between bins. The team evaluated which binning

[13] The Python Exploratory Spatial Data Analysis package includes the following nine binning methods: Jenks Natural Breaks, Fisher-Jenks Breaks, Jenks-Caspall Breaks, Head/Tail Breaks, Maximum Breaks, Equal Intervals, Quantile, Percentiles, and Standard Deviation from the Mean.

method could be consistently replicated as well as which method best mapped counties based on the relationships of the breaks to that indicator's means and medians (see Appendix D: Binning Methodology). This approach found that the Head/Tail Breaks classification method worked best for datasets that are heavily skewed (such as the percentage of households without a vehicle present), whereas the datasets that are not very skewed (such as the Gini Index) tended to be best depicted by either the Fisher-Jenks or Jenks-Caspall Breaks methods.

In two specific cases, the team used alternative criteria to select binning methodologies. Median household income can be segmented well by the Jenks-Caspall Breaks method, but a convention already exists for census data classifications: $0–25,000, $25,001–$50,000, etc. (an intuitive methodology that is similar to equal intervals). The population change dataset is provided by the U.S. Census as "net migration: total,"[14] which provides a positive (increase in population) or negative (decrease in population) number per 1,000 population. Large population changes in either direction could cause challenges to resilience. The team chose to represent the population change data as standard deviations from the mean, where less change is preferred to more change (regardless of whether the change is positive or negative).

After binning all 20 indicator datasets into five bins, the research team created choropleth maps[15] using color to illustrate each of the five bins.

Limitations and Benefits of Analysis

Limitations

Following are discussions of limitations concerning this approach:

- **County-level analysis.** There are 3,220 counties (and county equivalents) in the United States.[16] While county-level analysis is useful from a national perspective, county-level data may mask some local issues. For instance, a county with populations of older adults and individuals with disabilities that are similar to the national average may, in fact, have areas within the county that have populations with significantly higher levels of those attributes, affecting their ability to prepare and respond to disasters, for example, in the ability to quickly comply with evacuation orders.
- **Open source data.** For many of these indicators, more specific data may be available from proprietary sources. For example, a more specific indicator for determining healthcare capacity in a county would be the number of hospital beds per county. While this information is available, it must be purchased through the American Hospital Association. In addition, customized data on the hospitality industry, including hotel rooms by county, can be obtained from hospitality industry business intelligence companies who charge subscription fees for data access and analysis. The research team chose not to purchase any datasets to ensure that counties could find the data for their county at no cost.
- **Incomplete national datasets.** Some datasets did not include data for every county. The U.S. Census's primary datasets do not include results for many of the U.S. territories, including Guam, the U.S. Virgin Islands, American Samoa, and the Commonwealth of the Northern Mariana Islands. Data for Puerto Rico, also a U.S. territory, are available within most Census datasets. In other datasets,

[14] *U.S. Census Bureau*. https://www.census.gov/glossary/#term_Netmigration, accessed April 6, 2018.

[15] P. Longley, M. De Smith, and M. Goodchild, 2015, "Classification and Clustering," *Geospatial Analysis — A Comprehensive Guide*. Available at http://www.spatialanalysisonline.com/HTML/?classification_and_clustering.htm, accessed March 20, 2018.

[16] USGS (U.S. Geological Survey), undated, *How Many Counties Are There in the United States?* Available at https://www.usgs.gov/faqs/how-many-counties-are-there-united-states, accessed July 22, 2019.

data for Puerto Rico are provided separately, and in four cases[17] are not provided at all. Territories other than Puerto Rico may face some of the toughest challenges to resilience in the United States, but have not been assessed in this report because the data are not included in national datasets.[18]

- **Binning breaks are mathematically determined and are not a scorecard of resilience.** While the binning of data helps visually communicate large amounts of data by grouping data values into similar categories, the relationships of the specific bins to resilience outcomes would benefit from further research.
- **Hazard risk not included.** Hazard risk was not a factor in this analysis. The research team focused on identifying pre-disaster conditions that serve to forecast resilience to a range of hazards and risks. To factor in hazard risk, many national, state, and local assessments of risk can be overlaid onto this analysis.
- **No assessment of community capacity.** This analysis does not include data on a community's capacity to respond to a disaster relative to these indicators; for example, whether counties with relatively lower levels of hospitals per capita and lower levels of medical professions have developed surge capacity support for medical services by training the public, supporting volunteer programs, or investing in mobile clinics.

Benefits

The benefits of our approach in this analysis are highlighted in the following:

- **Existing peer-reviewed research.** Rather than positing a new model for community resilience, the analysis in this paper draws exclusively from the current body of research on community resilience. All of the community resilience research used in this analysis was peer-reviewed by experts before being published. The peer review process helps to ensure that the research methodologies are valid.
- **Commonly used indicators suggest some research agreement.** By identifying the commonly used indicators across multiple community resilience methodologies, this analysis identifies areas where researcher approaches have coalesced, indicating some agreement on community resilience indicators.
- **Focus on individual indicators.** Rather than using a construct of community functioning which aggregates indicators into domains, categories, or indices, this analysis focuses on the individual indicators. This approach provides the ability to identify specific areas that need to be addressed in order to improve resilience.
- **Relative assessment.** This analysis is not a scorecard of resilience; but provides a relative assessment of community resilience indicators. All communities can take steps to improve their resilience.
- **Choropleth maps help communicate results and allow for additional analysis.** Choropleth maps, maps with geographic areas that are color-coded or patterned based on values, help communicate the data and support analysis of these large and complex geographic datasets.
- **Broad application of findings.** In addition to helping FEMA NIC deliver community resilience TA tailored to the needs of a given community, this analysis can be used by many FEMA program areas and state, local, territorial, and tribal (SLTT) partners to support initiatives for all phases of emergency management, including mitigation, response, and recovery.

[17] Educational Attainment, Hospital Capacity, Affiliation with a Religion, and Population Change.
[18] U.S. Census Bureau, *Island Areas*. Available at https://www.census.gov/history/www/programs/geography/island_areas.html, accessed April 6, 2018.

- **Framework for further analysis.** Counties can use this analysis as a framework for obtaining more detailed data, including Census-tract data or related datasets available within the jurisdiction.

Community Resilience Indicators

Correlation Analysis

The research team conducted a correlation analysis to measure and describe the strength and direction of the relationships among the 20 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 Coefficient[19] 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 1 summarizes some highlights of the correlation analysis. The chart of Pearson Correlation Coefficients can be found as Appendix E.

Table 1: Correlation Relationships

Indicator	Positively Correlates With	Negatively Correlates With
Age (adults over 65)	• Disability (r = 0.41)	• Population Change (r = -0.34) • Single-Parent Households (r = -0.31).
Lack of High School Diploma	• Single-Parent Household (r = 0.53) • Unemployment Rate (r = 0.50) • Lack of Health Insurance (r = 0.46) • Presence of Mobile Homes (r = 0.45) • Population with a Disability (r = 0.43) • Limited English Language Proficiency (r = 0.43) • Income Inequality (r = 0.37)	• Household Income (r = -0.59) • Medical Professional Capacity (r = -0.49) (access to healthcare)
Disability	• Presence of Mobile Homes (r = 0.48) • Lack of High School Diploma (r = 0.43) • Unemployment Rate (r = 0.41) • Age (r = 0.41)	• Household Income (r = -0.66) • Medical Professional Capacity (r = -0.34) (access to healthcare)

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

Indicator	Positively Correlates With	Negatively Correlates With
Limited English Language Proficiency	• Unemployment Rate (r = 0.52) • Lack of High School Diploma (r = 0.43) • Lack of Vehicle (r = 0.33)	• Household Income (r = -0.31)
Lack of Health Insurance	• Lack of High School Diploma (r = 0.46) • Presence of Mobile Homes (r = 0.37)	• Medical Professional Capacity (r = -0.41) (access to healthcare)
Lack of Vehicle	• Single-Parent Households (r = 0.59) • Unemployment Rate (r = 0.50) • Income Inequality (r = 0.39) • Lack of High School Diploma (r = 0.34) • Limited English Language Proficiency (r = 0.33)	• Home Ownership (r = -0.32) • Household Income (r = -0.30)
Unemployment Rate	• Single-Parent Households (r = 0.66) • Limited English Language Proficiency (r = 0.52) • Lack of High School Diploma (r = 0.50) • Lack of Vehicle (r = 0.50) • Disability (r = 0.41)	• Household Income (r = -0.50)
Single-Parent Household (of all family households)	• Unemployment Rates (r = 0.66) • Lack of Vehicle (r = 0.59) • Lack of High School Diploma (r = 0.53) • Income Inequality (r = 0.49)	• Household Income (r = -0.48) • Age (r = -0.31)
Presence of Mobile Homes	• Disability (r = 0.48) • Lack of High School Diploma (r = 0.45) • Lack of Health Insurance (r = 0.37)	• Household Income (r = -0.42) • Medical Professional Capacity (r = -0.39) (access to healthcare)

County-level Maps

The research team created national choropleth maps (Figure 1–Figure 20), with every county shaded based on a five-color scale (Table 2). The scale uses colors to indicate potentially higher and lower relative levels of resilience. Yellow is at the top of the scale indicating relatively higher relative resilience followed by green, and then deepening colors of blue to indicate potentially lower relative levels of resilience. Gray-colored counties indicate that no data were available for that indicator within the dataset used for that indicator. These maps show areas of the country that have high or low relative data points for that specific indicator.

Table 2. Color Scale for Choropleth Maps

	Potentially high disaster resilience
	Potentially low disaster resilience

Each indicator page includes the map, indicator data source, binning method, number of counties in each bin (shown in the parenthesis in the legend), the national average value for the indicator, and findings. Unless otherwise noted, the data source for the indicators is the U.S. Census Bureau's American Community Survey (ACS) five-year estimates for 2014–2018. The Census Bureau updates the ACS's five-year estimate on an annual basis each December; so as of the date of this report, 2014–2018 data are the most current data available. The primary advantage of using multiyear estimates is the increased statistical reliability of the data compared with that of single-year estimates, particularly for small geographic areas and small population subgroups.

All maps and data can be found on the Resilience Analysis and Planning Tool (RAPT). RAPT data layers include the 20 county-level community resilience indicators identified in the CRIA as well as census-tract level information for 12 of those indicators, infrastructure information drawn from the Homeland Infrastructure Foundation-Level Data (HIFLD) Subcommittee, and hazards, including real-time weather forecasts, historic disasters, and projected hazard risk. RAPT is available at https://bit.ly/ResilienceAnalysisandPlanningTool.

RAPT is an effective tool to help emergency managers and community leaders:

- Visually assess challenges to resilience to help design more relevant community outreach, evaluate mitigation plans and emergency operations plans, and better understand the impacts of potential hazards;
- Provide input data when developing the Threat and Hazard Identification and Risk Assessment (THIRA) and the Stakeholder Preparedness Review (SPR) and grant submissions; and
- Obtain relevant community information to prioritize response and recovery efforts.

RAPT is available online at http://bit.ly/ResiliencePlanningTool.

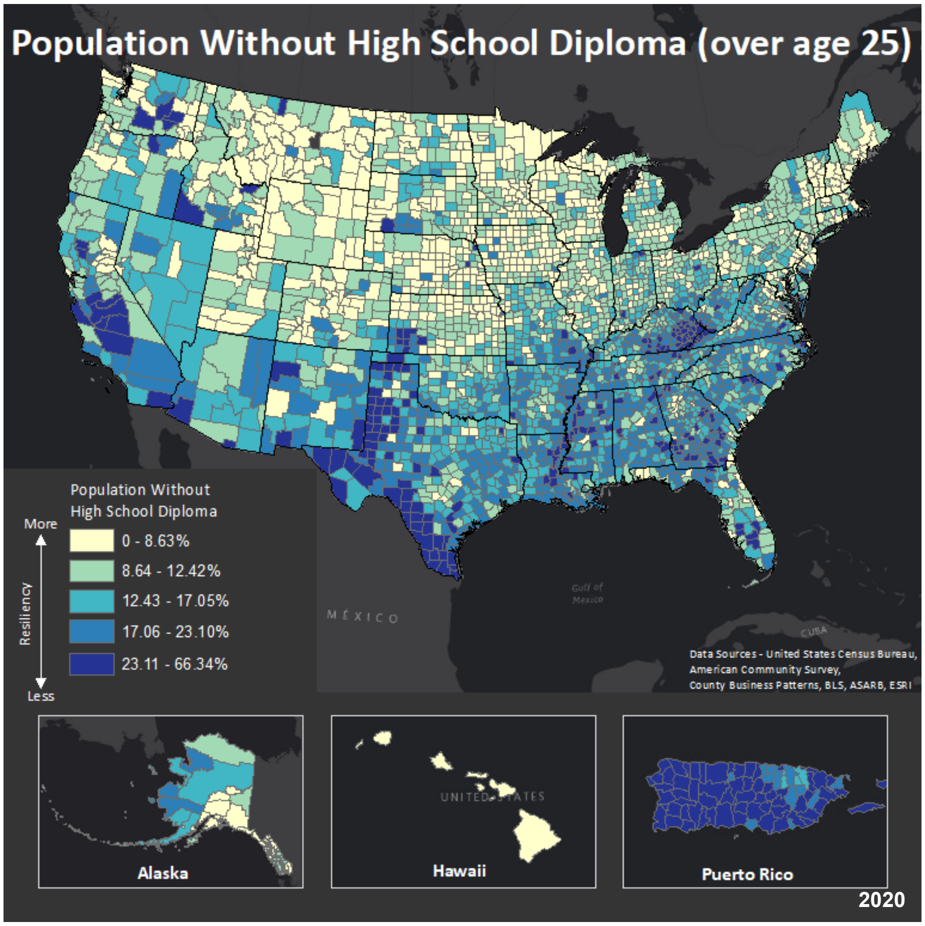

Figure 1. *Educational Attainment*: Lack of High School Diploma in Adults over Age 25

Data Source: ACS 2014-2018 five-year estimates, Table S1501

Binning Method: Jenks-Caspall Breaks

National Average: 12.3 percent of the U.S. adult population over the age of 25 does not have a high school diploma or General Education Diploma (GED).

Findings:

- Across the Southeast, more than half the counties in many states are in the lower two bins, which means more than 15.41 percent of the county population over age 25 do not have a high school diploma. These states include Mississippi (68% of counties are in the lower two bins), Louisiana (63%), Alabama (60%), Georgia (57%), and Kentucky (55%).
- In Texas, in approximately one quarter of all counties (primarily those along the border with Mexico), more than 23.11 percent of the population over 25 does not have a high school diploma.
- In Puerto Rico, 23.11 percent of the population over 25 in 63 of 78 counties does not have a high school diploma.

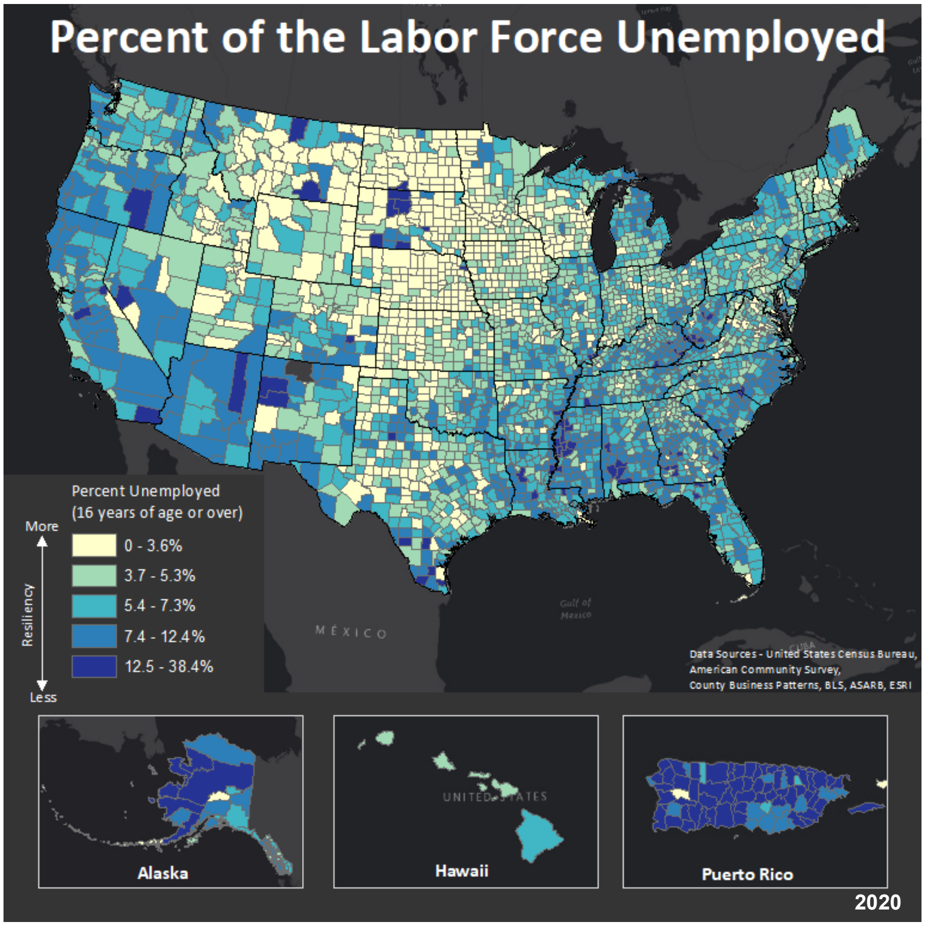

Figure 2. *Unemployment Rate*: Percent of the Labor Force That Is Unemployed

Data Source: ACS 2014-2018 five-year estimates, Table S2301

Binning Method: Fisher-Jenks Breaks

National Average: 6.02 percent of the employable U.S. population over 16 years of age is unemployed.

Findings:

- Unemployment is generally low in the Midwest, although six counties in South Dakota report high levels of unemployment, above 12.5 percent.
- About one in four of the counties in Mississippi (28%) and Alabama (24%) face double-digit unemployment.
- Puerto Rico is facing overall high unemployment with 59 of 78 municipios having 12.5 percent or greater unemployment.
- More than 93% of the counties in Arizona have an unemployment rate greater than the national average.

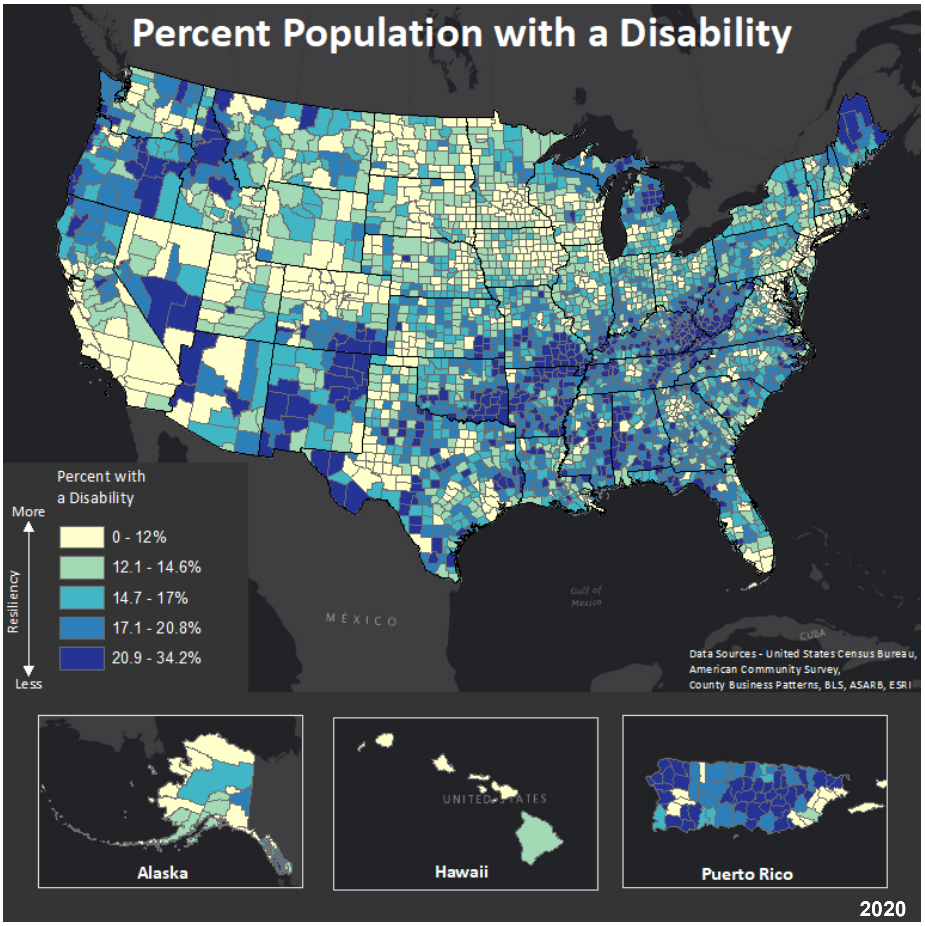

Figure 3. *Disability*: Percent of the Population with a Disability

Data Source: ACS 2014–2018 five-year estimates, Table S1810

Binning Method: Jenks-Caspall Breaks

National Average: 12.6 percent of the U.S. population has a disability.

Findings:

- States with the highest concentrations of counties having more than 20.9 percent of the population with a disability include Arkansas (53% of counties), Kentucky (44%), New Mexico (42%), and West Virginia (40%).
- States where more than half their counties report 17.1 percent or more of their populations with a disability include Arkansas (84% of counties), West Virginia, (84%), Tennessee (74%), Kentucky (73%), Alabama (67%), Mississippi (62%), Oregon (58%), New Mexico (58%), and Oklahoma (57%).
- Forty-two of 78 counties in Puerto Rico reported populations with disabilities at a rate of 20.9 percent or greater.

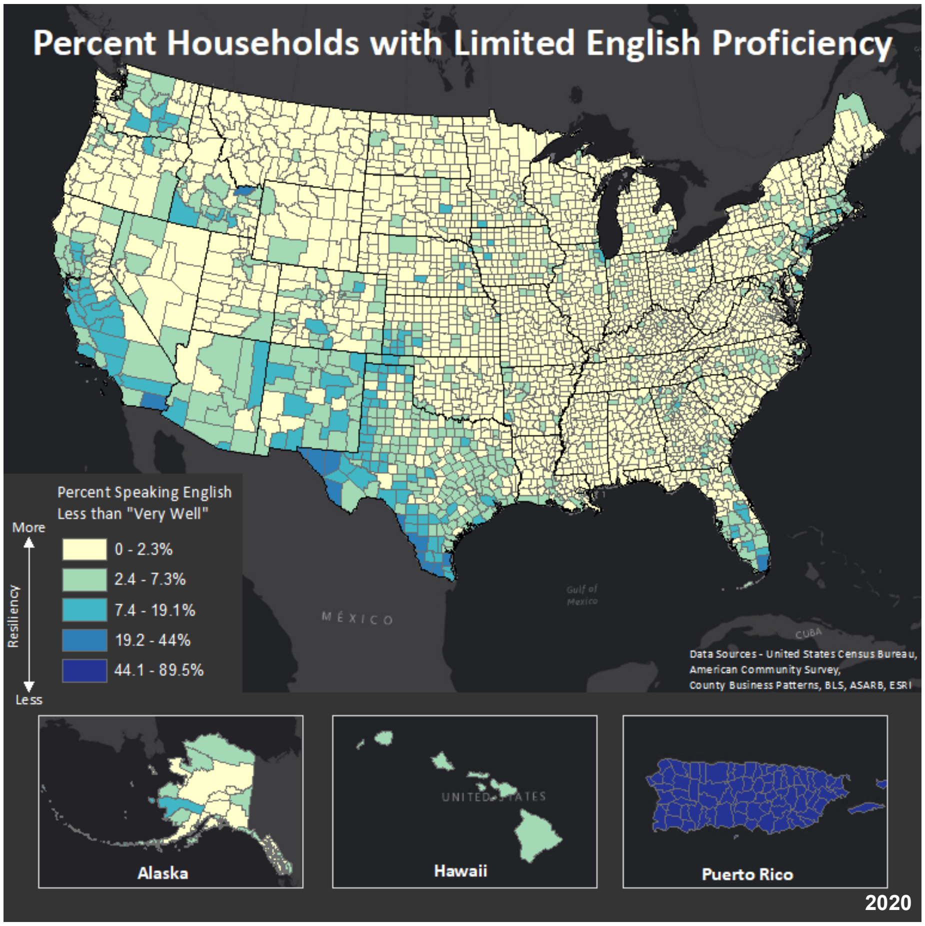

Figure 4. *English Language Proficiency*: Percent of Households with Limited English Proficiency

Data Source: ACS 2014-2018 five-year estimates, Table S1602

Binning Method: Jenks-Caspall Breaks

National Average: 4.4 percent of all U.S. households are considered a "limited English-speaking household" (where no member who is 14 years and older speaks only English or speaks English "very well").

Findings:

- Across all municipios in Puerto Rico, more than 44.1 of households have limited English proficiency. In 1991 Spanish was declared the official language of Puerto Rico.[20]
- In Texas, almost one quarter of counties (23%) have more than 7.4 percent of households that speak limited English.
- In California in 22 of 58 counties (38%), more than 7.4 percent of households are limited English-speaking households. In Imperial County 23 percent of households are limited English-speaking.
- South Florida has a concentration of counties with limited English-speaking households, with Miami-Dade County the highest at 25 percent.

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[20] *The Washington Post*, 1991, "Puerto Rico Makes Spanish Official Language," April 6. Available at https://www.washingtonpost.com/archive/politics/1991/04/06/puerto-rico-makes-spanish-official-language/50b6c2a9-563e-4f8b-a00e-1b65b80a0a6e/?utm_term=.ac67c869cb48, accessed April 6, 2018.

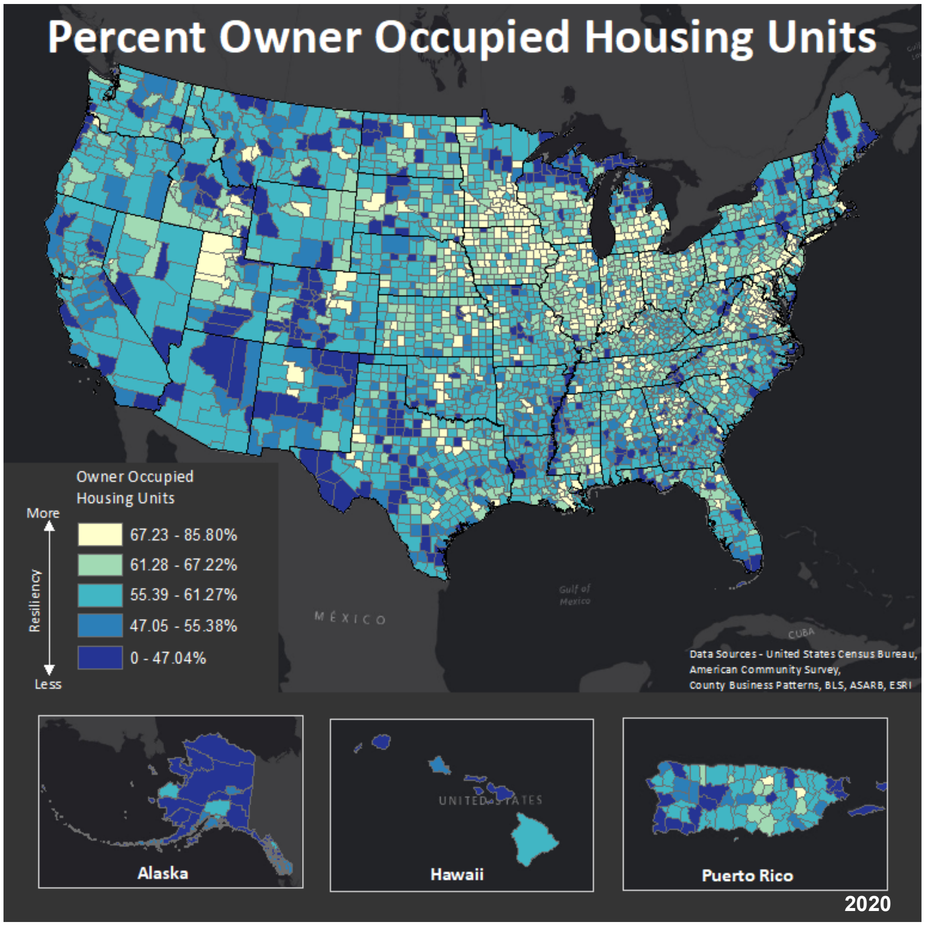

Figure 5. *Home Ownership*: Percent of Owner-Occupied Housing Units

Data Source: ACS 2014-2018 five-year estimates, Table DP04

Binning Method: Fisher-Jenks Breaks

National Average: 63.8 percent of homes in the United States are occupied by the owner.

Findings:

- In almost two-thirds of U.S. counties (65%), more than half of housing units are owner-occupied.
- The states where two out of three or more of counties have home ownership levels below 55.39 percent (lowest two bins) include Hawaii (100%), Alaska (86%), California (72%), New Mexico (66%), and Arizona (66%).
- Several counties making up the City of New York fall in the lower ranges of home ownership, including Bronx County (19%), New York County (21%), and Kings County (28%).

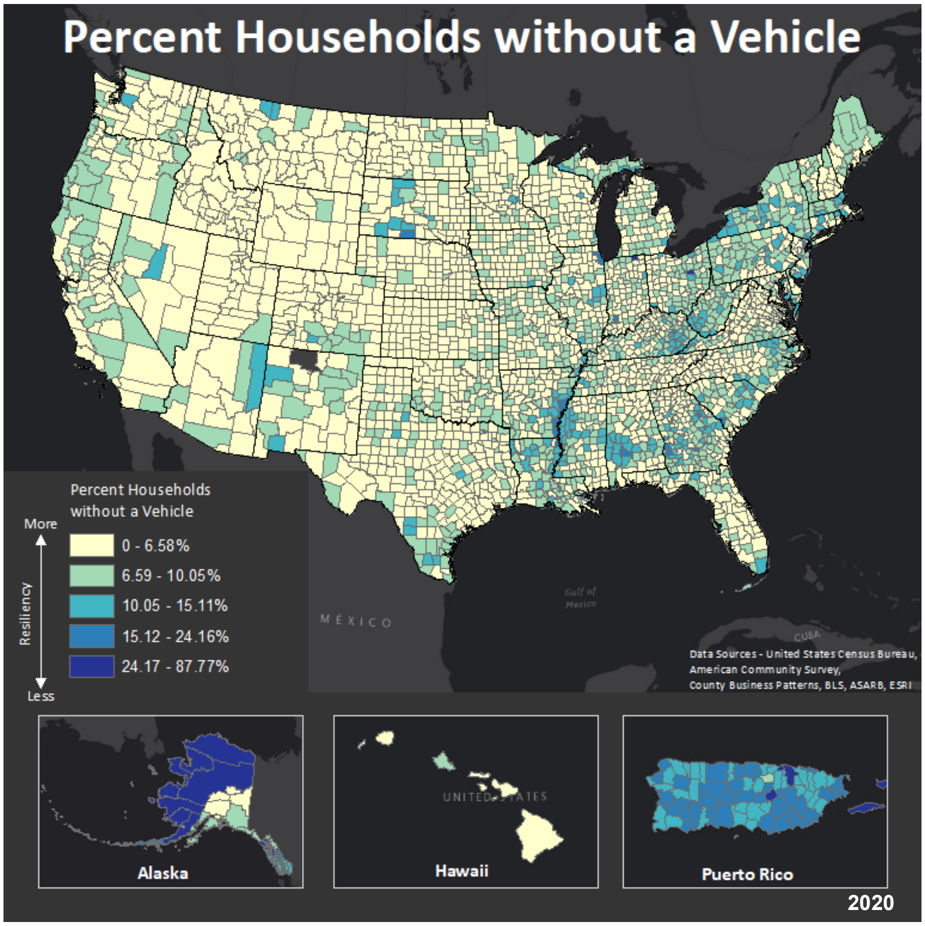

Figure 6. *Mobility*: Percent of Households without a Vehicle

Data Source: ACS 2014-2018 five-year estimates, Table B08201

Binning Method: Head Tail Breaks

National Average: 8.7% percent of U.S. households are without a vehicle.

Findings:

- Several states have a relatively higher numbers of counties where one in ten (10.05%) or more of households do not have access to a vehicle. These include Alaska (55% of counties); some states in the Northeast, including New Jersey (38%), Massachusetts (36%), New York (35%), Connecticut (25%), and Rhode Island (20%); and others in the Southeast, including Mississippi (22%), West Virginia (22%), and South Carolina (22%).
- In Puerto Rico, the data shows 43 municipios with rates of 15.12 percent of households and higher lacking access to a vehicle.
- Of the 9 U.S. counties where 40 percent or more households are without access to a vehicle, 6 are in rural Alaska and 3 are in the extremely urban counties that make up the City of New York: New York County, Kings County, and Bronx County.

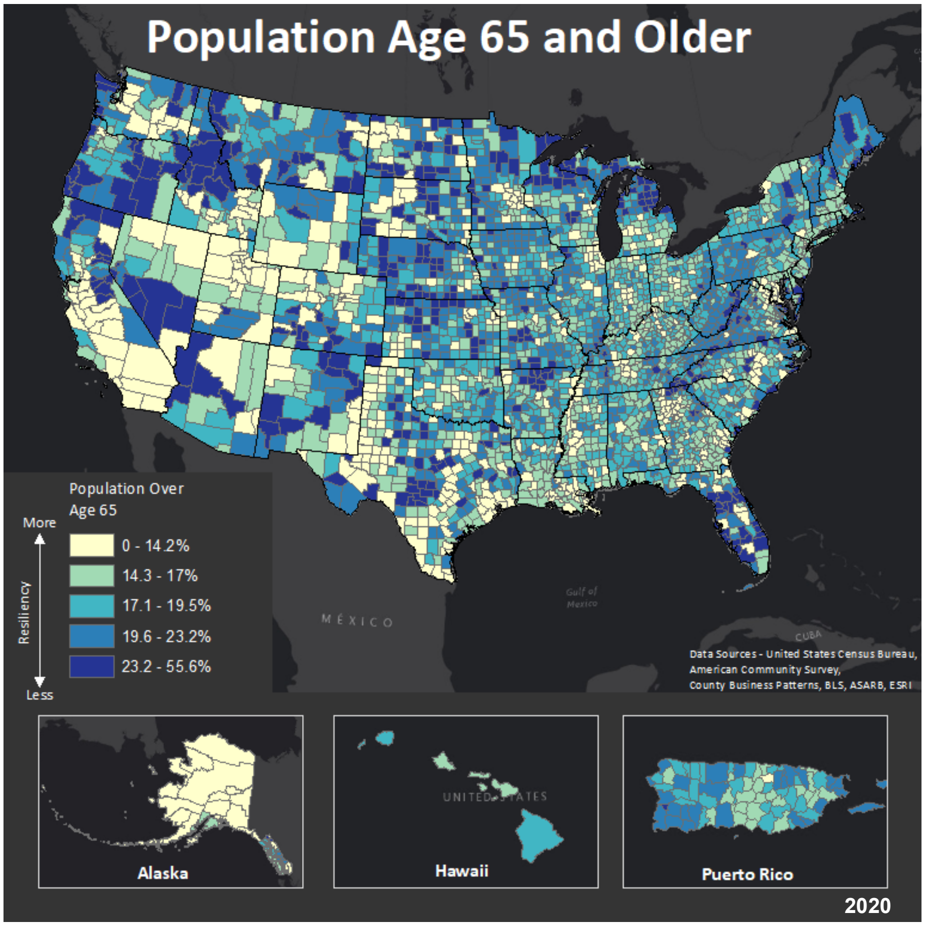

Figure 7. *Age*: Population Age 65 and Older

Data Source: ACS 2014-2018 five-year estimates, Table S0101

Binning Method: Jenks-Caspall Breaks

National Average: 15.2 percent of the U.S. population is 65 years of age or older.

Findings:

- Twenty of Florida's 67 counties have populations where 23.2 percent or more of the residents are 65 years of age or older. In eight of these counties, 30 percent or more of the population is 65 years or older.
- Other states where more than half of counties have populations where 19.6 percent or more of the residents are 65 or older include Maine (69% of counties), West Virginia (64%), Montana (63%), Nebraska (62%), North Dakota (60%), Iowa (56%), and Oregon (53%).

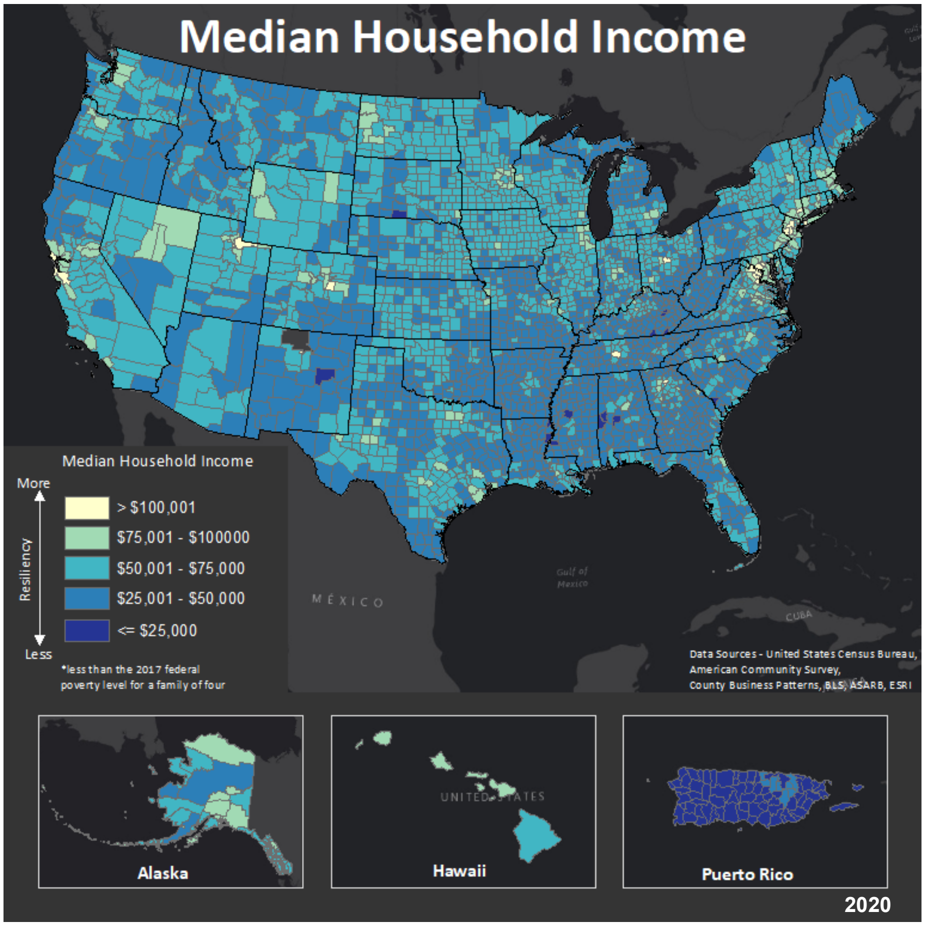

Figure 8. *Household Income*: Median Household Income

Data Source: ACS 2014-2018 five-year estimates, Table S1903

Binning Method: Manual, based on Census breaks

National Average: The median household income in the United States is $60,273

Findings:

- Many states in the Southeast with high concentrations of counties with lower median incomes ($50,000 or lower) include: Mississippi (93% of counties), Arkansas (92%), West Virginia (91%), Alabama (85%), Tennessee (79%), Georgia (78%), South Carolina (76%), and Kentucky (75%).
- Several states in the Southwest and Midwest have more than 60% of counties with low median income ($50,000 or lower), including New Mexico (78% of counties), Oklahoma (62%), and Michigan (62%).
- Puerto Rico has a particularly low median household income relative to other parts of the United States. Seventy of 78 municipios within Puerto Rico are in the lowest bin (0–$25,000).

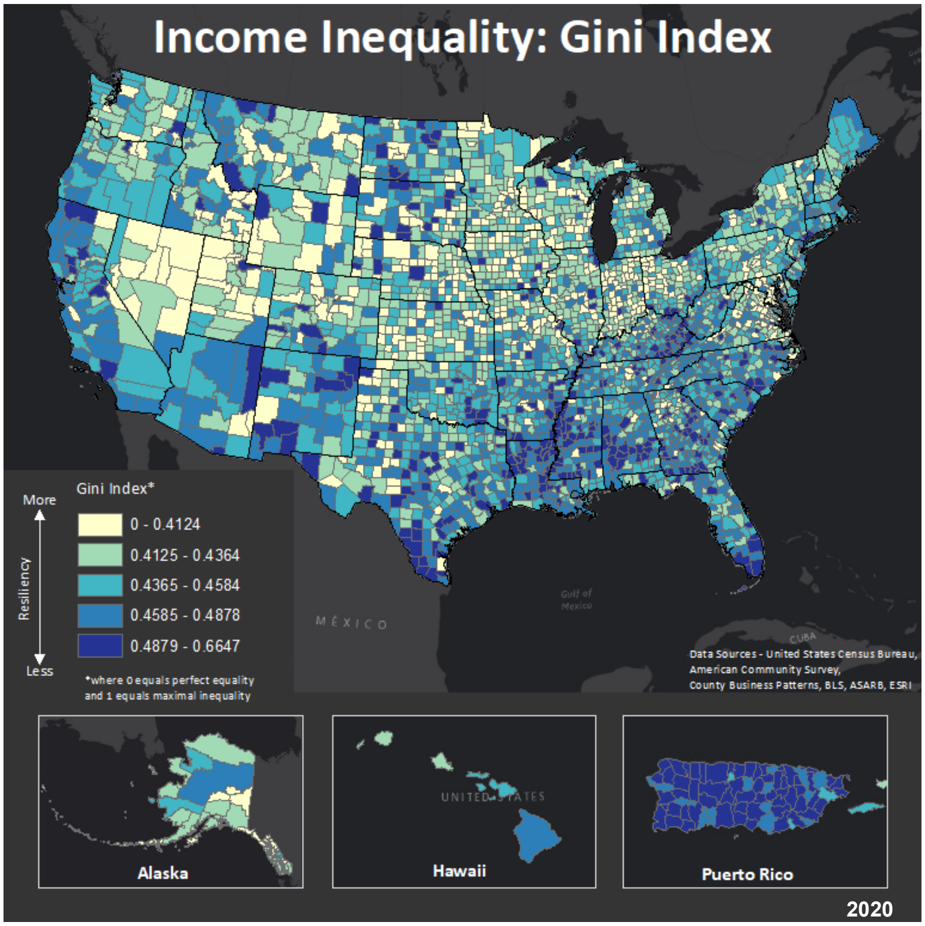

Figure 9. *Income Inequality*: Gini Index

Data Source: ACS 2014-2018 five-year estimates, Table B19083

Binning Method: Jenks-Caspall Breaks

National Average: The average Gini score in the United States is 0.48. "Perfect" income equality is 0, and "perfect" income inequality is 1.

Findings:

- States where more than one-quarter of counties have Gini Index rates over 0.4879 (greater income inequality) include Louisiana (41% of counties), Mississippi (37%), and New Mexico (22%).
- Puerto Rico is the most concentrated area of income inequality where 59 of 78 counties (76%) have index numbers of 0.4879 or higher.
- States with high percentages of counties with Gini Index rates below 0.4124 (greater equality) include Nevada (53% of counties), Indiana (46%) Alaska (45%), Utah (45%) and Maryland (42%).

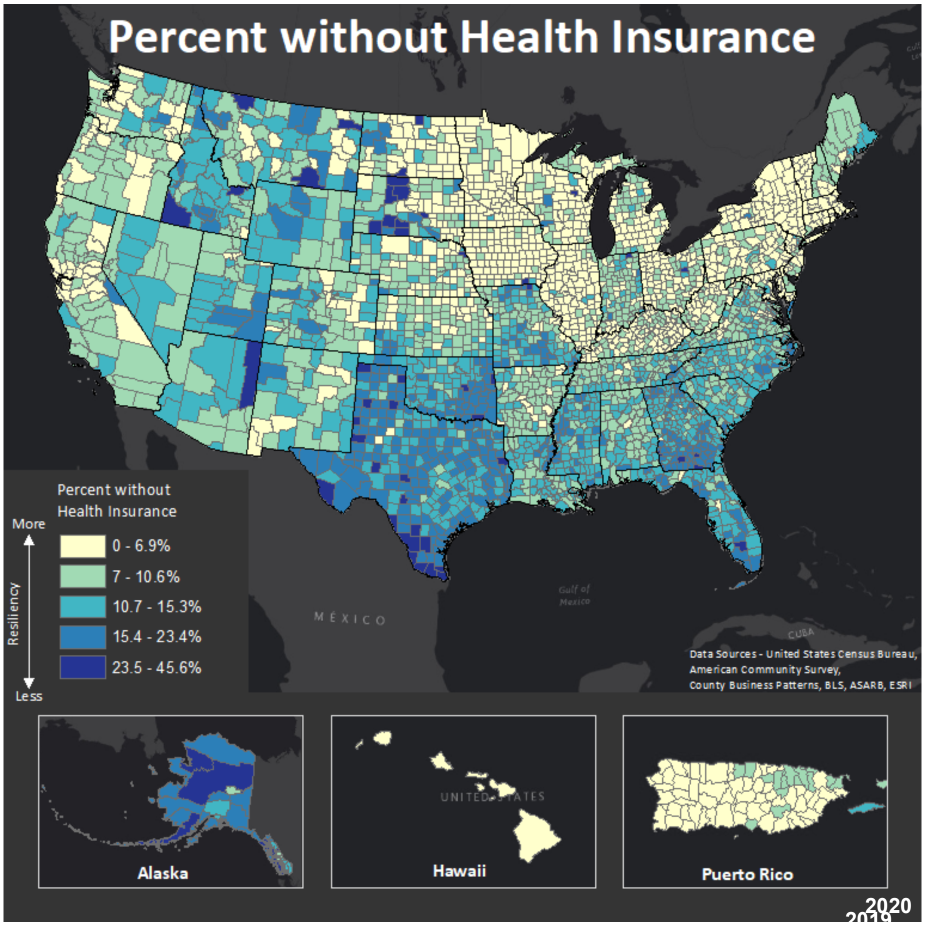

Figure 10. *Health Insurance*: Percent without Health Insurance (Public or Private)

Data Source: ACS 2014–2018 five-year estimates, Table S2701

Binning Method: Fisher-Jenks Breaks

National Average: 9.4 percent of the U.S. population does not have health insurance.

Findings:

- Health insurance coverage is most prevalent in the Northeast and Midwest, with many counties having populations without health insurance below 10.7 percent. Hawaii and Puerto Rico also have few without coverage.
- In a total of 166 of Texas's 254 counties (65%), 15.4 percent or more residents lack health insurance; and of those, 20 counties have populations where 23.5 percent or more lack coverage.
- More than 40% of counties in Oklahoma and Georgia have populations where 15.4 percent or more residents lack health insurance.
- Alaska has the lowest rates of coverage overall with15.4 percent or more of the population without coverage in 22 of 29 counties (76%), and 23.5 percent or more of the population without coverage in 6 counties.

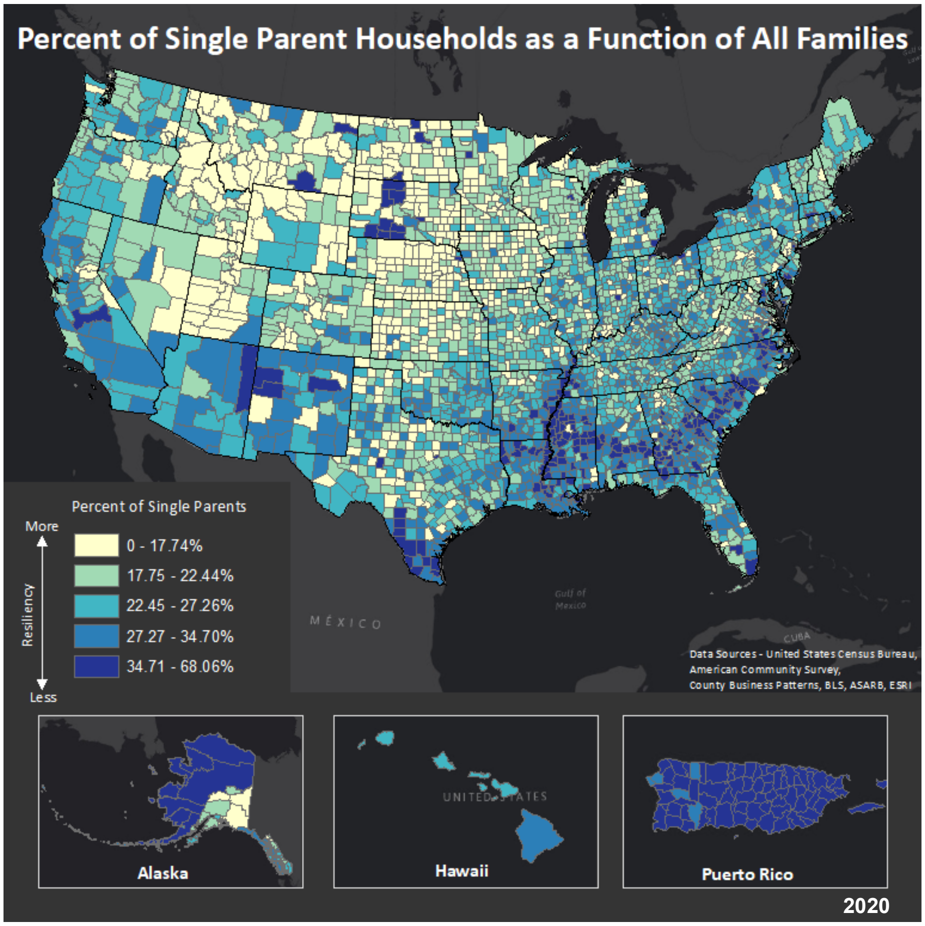

Figure 11. *Single-Parent Households*: Percent of Single-Parent Households as a Function of All Families

Data Source: ACS 2014–2018 five-year estimates, Table DP02

Binning Method: Jenks-Caspall Breaks

National Average: 32.1 percent of U.S. family households are single-parent households.[21]

Findings:

- In several states in the Southeast, 27.27 percent or more of all family households are single-parent households in the majority of their counties, including Mississippi (78%), Louisiana (75%), South Carolina (70%), Delaware (67%), and Georgia (58%).
- New Mexico also has a relatively high rate of single-parent households when compared with other states in Southwest with almost 6 in ten counties (57%) having more than 27.27 percent of households headed by a single parent.
- In Puerto Rico, 69 of 78 municipios have more than 34.71 percent of family households headed by a single parent.

[21] Approximately 65% of U.S. Households are considered "family" households. Source: U.S. Census Bureau, *American Community Survey 2018 5-year Estimates, Table DP02*.

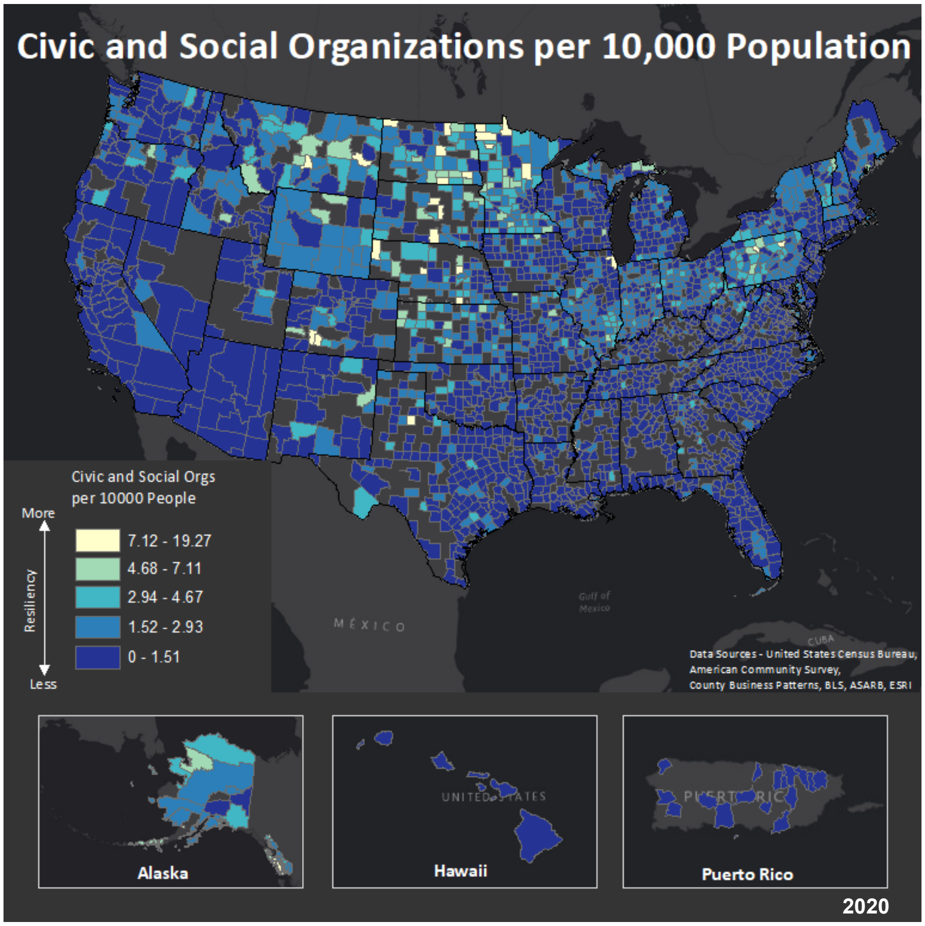

Figure 12. *Connection to Civic and Social Organizations*:
Civic and Social Organizations per 10,000 Population

Data Source: U.S. Census Bureau, 2016 County Business Patterns, Table 00A1, NAICS Code 8134

Binning Method: Head/Tail Breaks

National Average: The U.S. averages 0.83 civic and social organizations per 10,000 population.

Findings:

- Most of the counties in Georgia (77 of 91 counties) have less than 1.52 organizations per 10,000 population.
- In North Dakota, 55 percent of counties report 2.94 or more civic and social organizations per 10,000 population.
- Other states with high concentrations of civic and social organizations (2.94 organizations or more) include Minnesota (48% of counties), Alaska (47%), and South Dakota (39%).

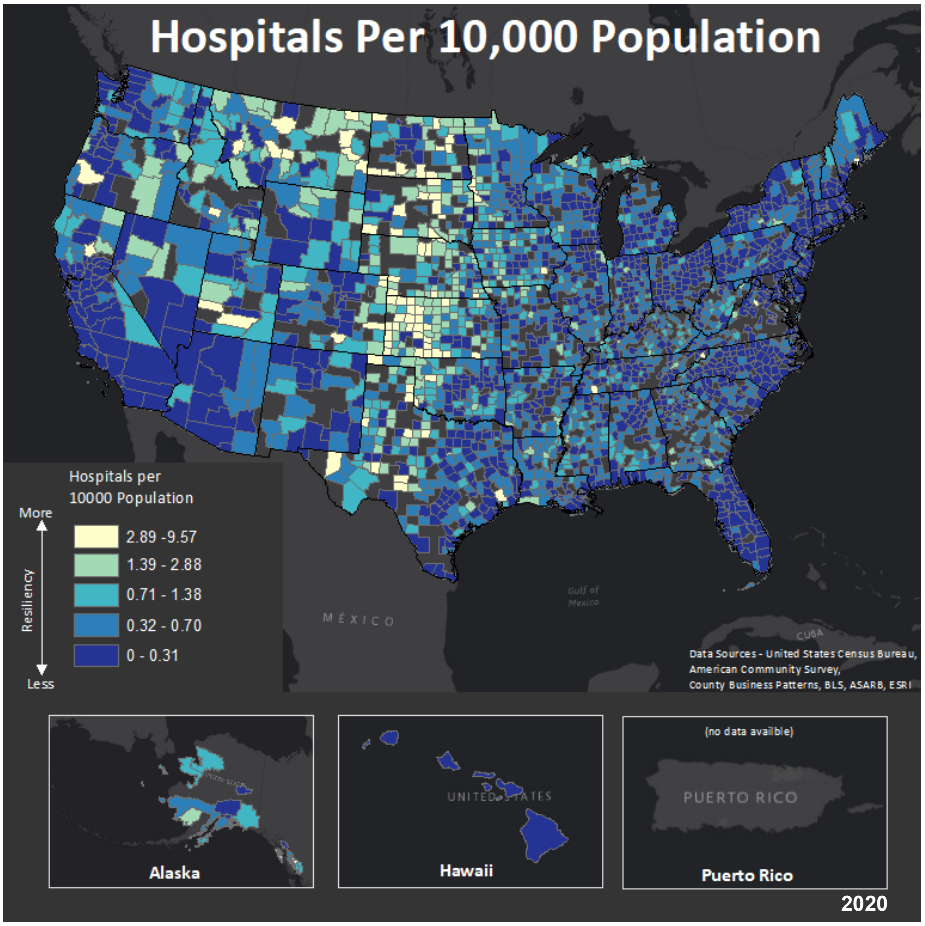

Figure 13. *Hospital Capacity*: Hospitals per 10,000 Population

Data Source: U.S. Census Bureau, 2016 County Business Patterns, Table 00A1, NAICS Code 622110

Binning Method: Jenks-Caspall Breaks

National Average: The U.S. has an average of .17 hospitals per 10,000 population.

Findings:

- Generally, areas with higher ratios of hospitals per 10,000 population appear in the Midwest and upper West. In Kansas, 48 of 95 counties have more than 1.39 hospitals per 10,000 population.
- States with the lowest ratios of hospitals to population (0.31 hospitals per 10,000 population or lower) include Delaware (100%), Hawaii (100% of counties), Rhode Island (100%), Connecticut (87%), Massachusetts (86%), New Jersey (85%), and Maryland (78%).

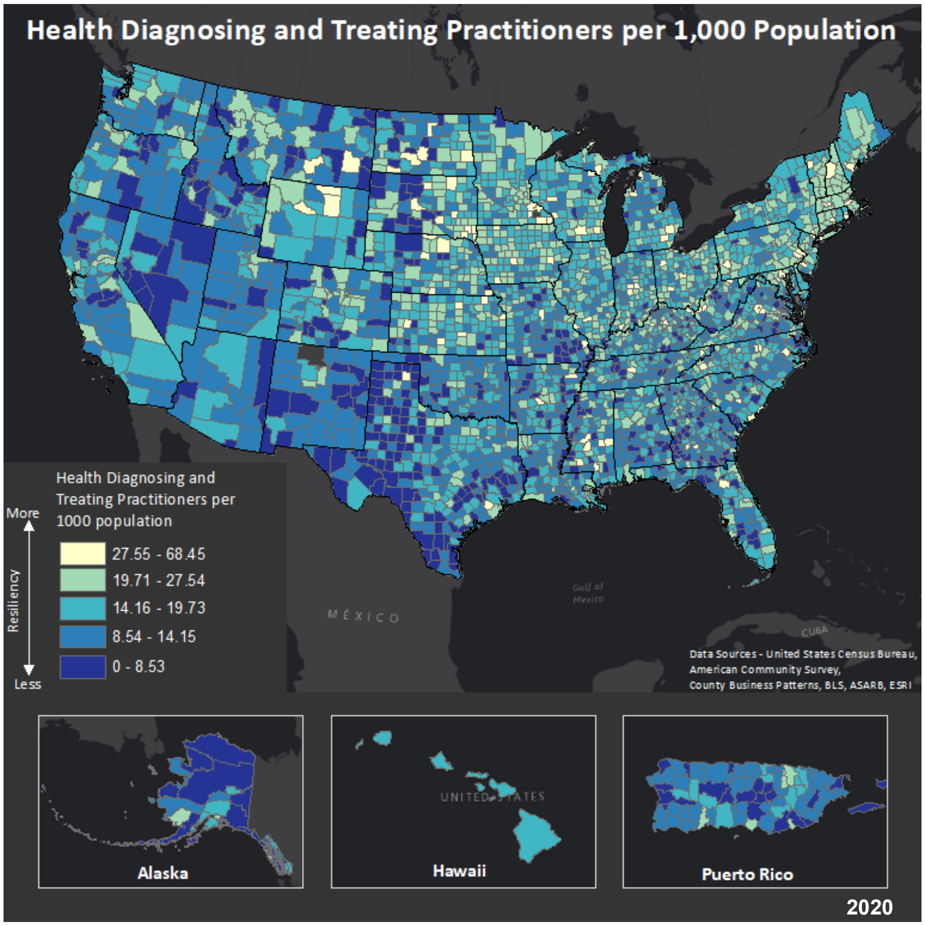

Figure 14. *Medical Professional Capacity*: Health Diagnosing and Treating Practitioners per 1,000 Population

Data Source: ACS 2014-2018 five-year estimate, Table S2401

Binning Method: Jenks-Caspall Breaks

National Average: The U.S. averages19 health-diagnosing and treating practitioners per 1,000 population.

Findings:

- The states in the Northeast and the eastern states of the Midwest (except Missouri) have relatively high levels of health practitioners per 1,000 people.
- The Southeast and Western states have higher numbers of counties in the lower two bins, with 14.15 or fewer practitioners per 1,000 population.
- Ten counties in Texas; three counties in Nevada, two counties in Georgia; and one county each in Hawaii, Idaho, Mississippi, Montana, Nebraska, New Mexico, Puerto Rico, and Utah report having zero health practitioners.

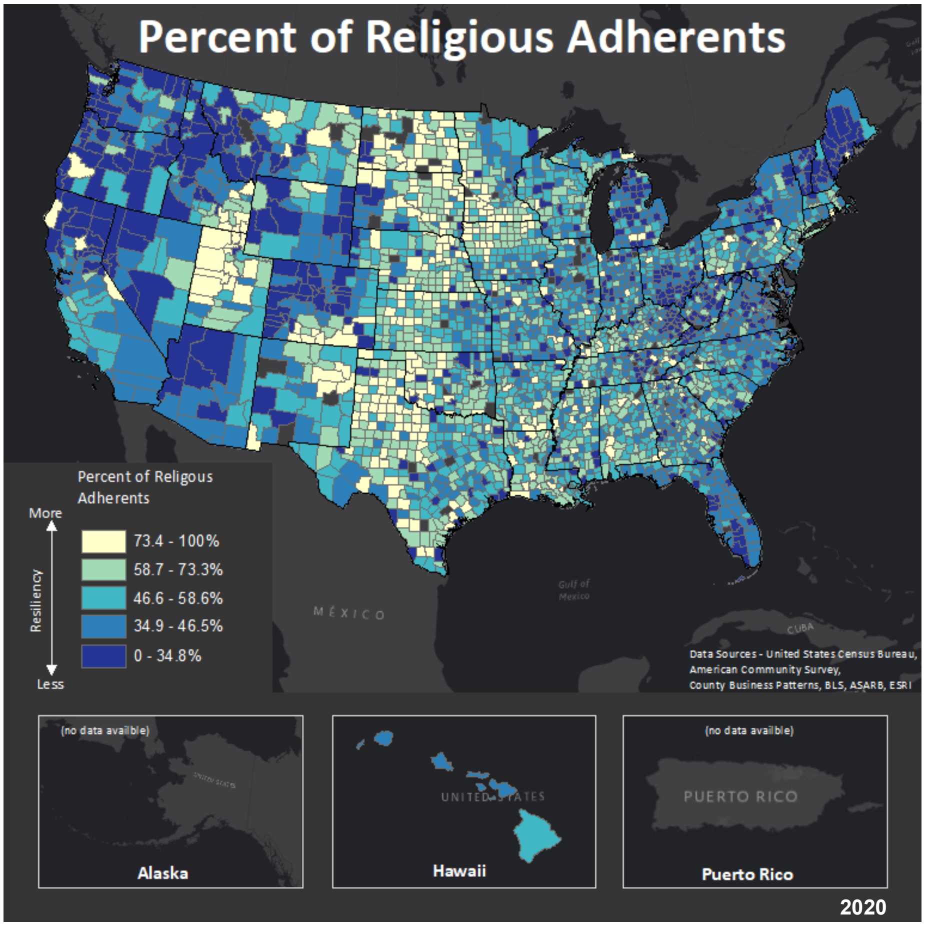

Figure 15. *Affiliation with a Religion*: Percent of Religious Adherents

Data Source: Association of Statisticians of American Religious Bodies, 2010 U.S. Religion Census

Binning Method: Jenks-Caspall Breaks

National Average: An average of 51.4 percent of a U.S. county's population are religious adherents.

Findings:

- The highest concentrations of religious adherents by county are in the central and southern United States.
- States with lower concentrations of religious adherents are along the two coasts, large portions of the West, Michigan, and Appalachia.
- States with particularly low levels of religious adherents (more than half of counties with 34.8 percent and lower religious adherents) include Maine (81% of counties), New Hampshire (70%), Vermont (64%), Oregon (64%), and Washington (61%).
- A cluster of counties with relatively low levels of religious adherents occurs in Appalachia, where Ohio borders West Virginia and Kentucky.

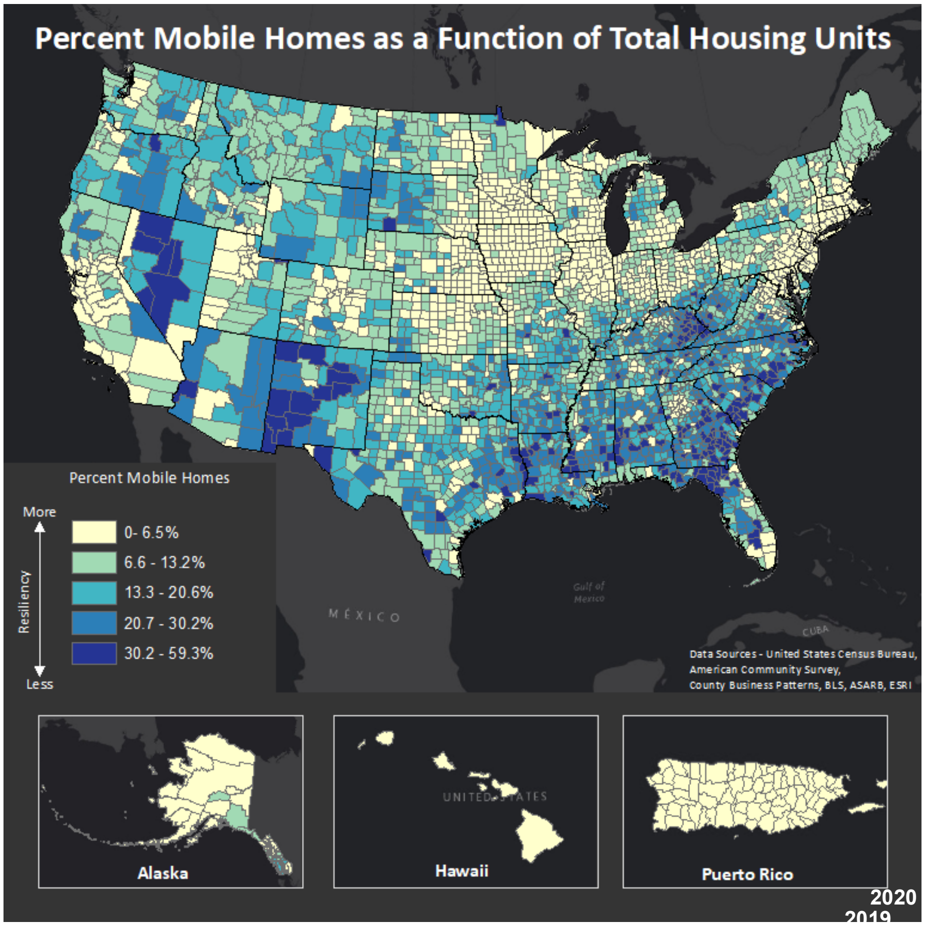

Figure 16. *Presence of Mobile Homes*: Percentage of Mobile Homes as a Function of Total Housing Units

Data Source: ACS 2014-2018 five-year estimates, Table DP04

Binning Method: Fisher-Jenks Breaks

National Average: 6.2 percent of housing units in the United States are mobile homes.

Findings:

- Higher concentrations of mobile homes (where 20.7 percent or more of total housing are mobile homes) are scattered across the Southeast, Southwest, and West.
- There are four states where more than a quarter of the counties have mobile homes representing 30.2 percent or more of the housing stock: Nevada (35% of counties), South Carolina (34%), Florida (31%), and Georgia (30%).
- There are 7 states in the Southeast where more than 4 out of 10 counties have mobile homes accounting for 20.7 percent or more of the housing stock: South Carolina (60.86% of counties), Alabama (55%), Mississippi (54%), Georgia (53%), North Carolina (50%), Kentucky (48%), and Florida (46%).
- Arizona, New Mexico, and Nevada all have a high percentage of counties — at 60%, 57.57%, and 41.17%, respectively — in which 20.7 percent or more of their housing stock are mobile homes.

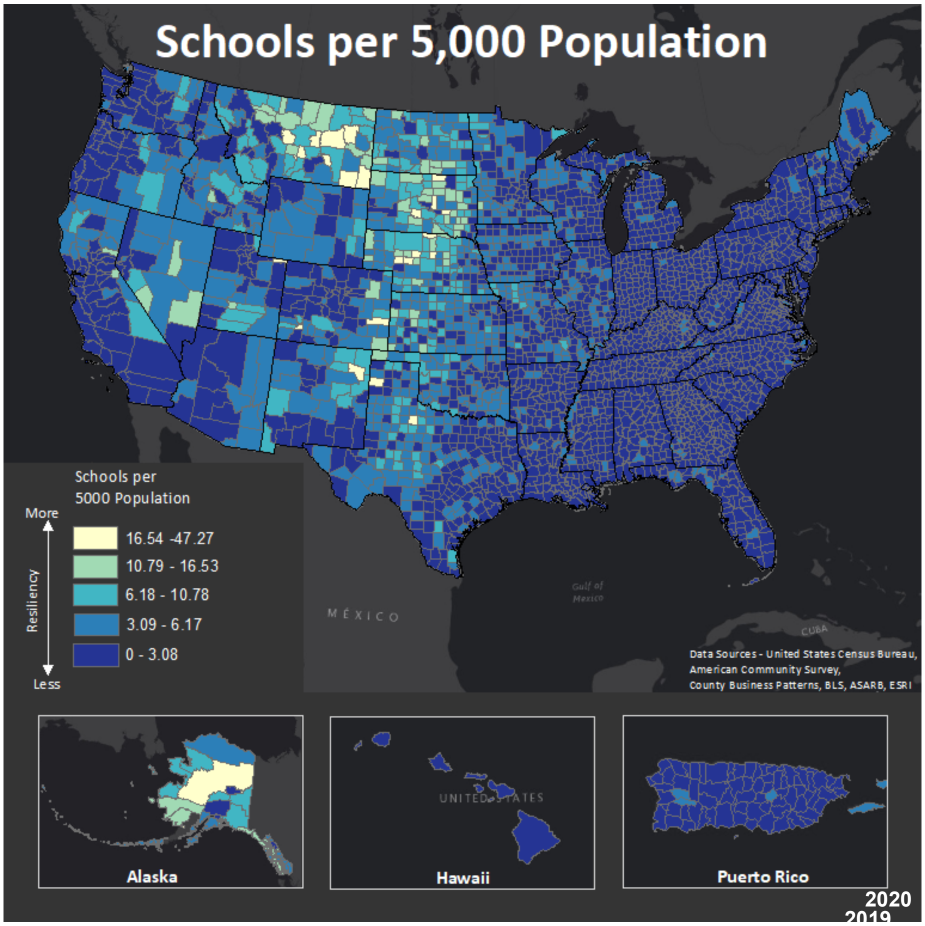

Figure 17. *Public School Capacity*: Schools per 5,000 Population

Data Source: 2017-2018 U.S. Department of Education, National Center for Education Statistics, Elementary/Secondary Information System.

Binning Method: Head/Tail Breaks

National Average: The United States averages 1.6 schools per 5,000 population.

Findings:

- Overall, the eastern United States and Puerto Rico have the lowest number of public schools by population.
- In Connecticut, Delaware, Hawaii, Indiana, Maryland, Massachusetts, New Jersey, Pennsylvania, Rhode Island, South Carolina, Tennessee, and Washington, D.C., every county has less than 3.08 schools per 5,000 population.
- One county in each of Mississippi, South Dakota, Texas and Hawaii has 0 public schools per 5,000 population.

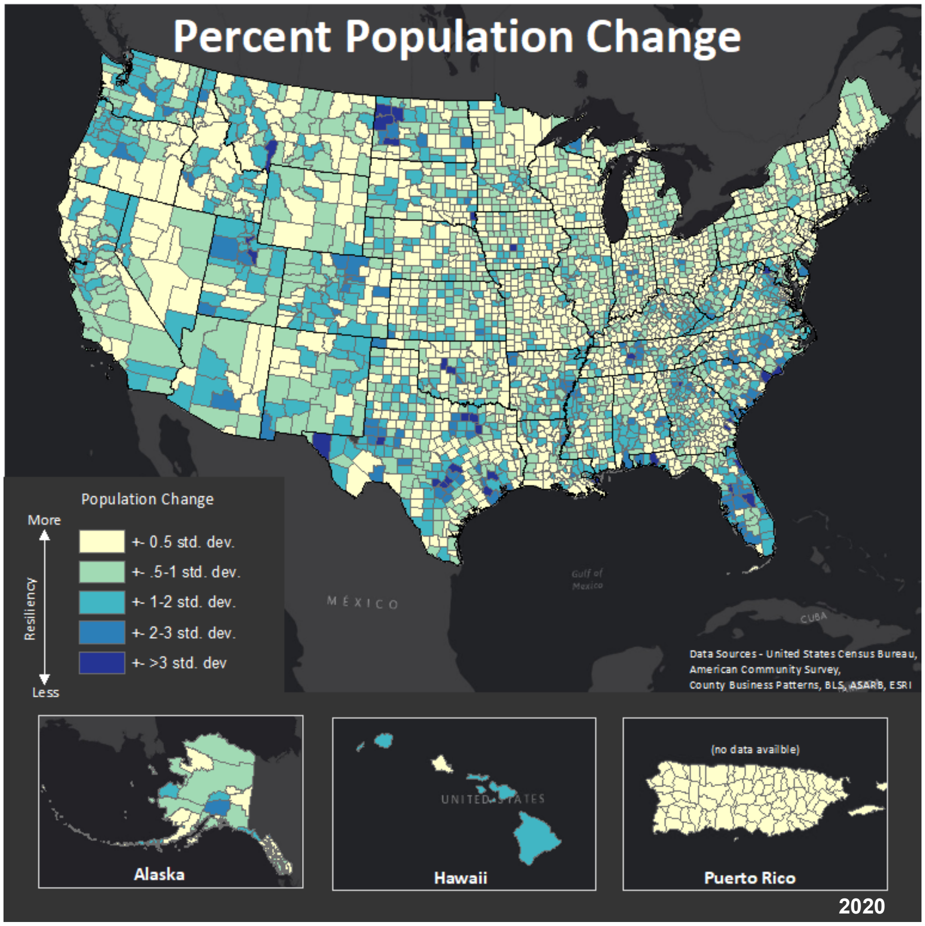

Figure 18. *Population Change*: Percent Population Change

Data Source: U.S. Census Bureau, Population Division, Table: Cumulative Estimate of the Components of Resident Population Change (PEPTCOMP): April 1, 2017, to July 1, 2018

Binning Method: Standard Deviation from the Mean

National Average: The average net migration per county in the United States is 0.72 standard deviation from the mean. On average, county populations have grown by 643 people from July 2017 to July 2018

Findings:

- County populations tend to be generally stable throughout most of the United States, although some areas of the country, particularly in the Southeast along the coast and in the Midwest, have higher changes in population.
- Three states in the Southeast have concentrations of counties with higher rates of population change more than 2 standard deviations away from the mean, including Florida (25.37% of counties), South Carolina (19.56%), and North Carolina (10%). These counties tend to be on the coast.
- A few states have counties with significant population change (3 or more standard deviations from the mean) including Texas (13 counties), Florida (4 counties), North Dakota (4 counties), and Georgia (3 counties).

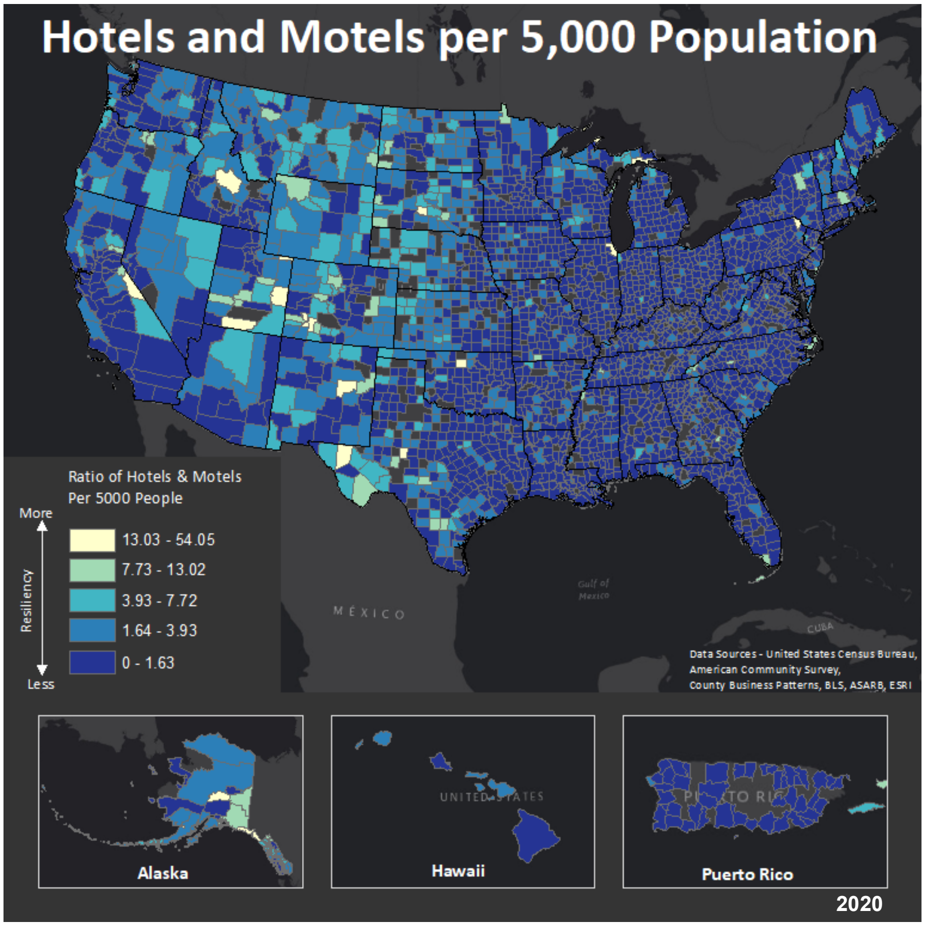

Figure 19. *Hotel/Motel Capacity*: Hotels and Motels per 5,000 Population

Data Source: U.S. Census Bureau, 2016 County Business Patterns, Table 00A1 NAICS Codes 72111/721120

Binning Method: Head/Tail Breaks

National Average: The United States averages .83 hotels and motels per 5,000 people.

Findings:

- Almost three-quarters of the counties in this dataset have less than 1.64 hotels or motels per 5,000 population.
- There are several states in the Midwest and Southeast where 90 percent or more of counties have fewer than 1.64 hotels or motels per 5,000 population including Indiana (95% of counties), Illinois (95%), Ohio (94%), and Kentucky (91%).

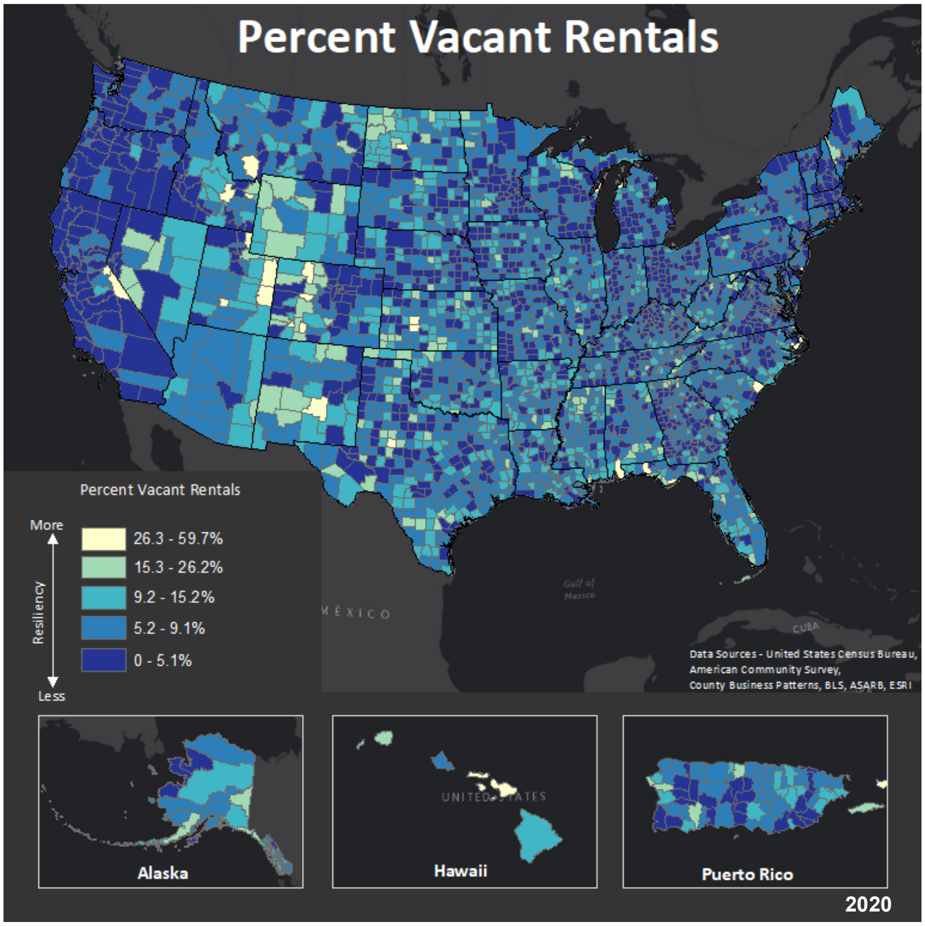

Figure 20. *Rental Property Capacity*: Percent Vacant Rentals

Data Source: ACS 2014-2018 five-year estimates, Table DP04

Binning Method: Fisher-Jenks Breaks

National Average: 6% percent rental vacancy rate on average in the United States.

Findings:

- The Northeast and West Coast have clusters of very low availability for rental housing, that is, below 5.2 percent.
- In several states, more than half of all counties have rental vacancy rates below 5.2 percent, including California (81%), Massachusetts (79%), Oregon (75%), New Hampshire (70%), Vermont (64%), Washington (64%), and Minnesota (51%).
- In several states on the hurricane-prone Southeast coast, close to 30 percent of counties have rental vacancy rates below 5.2 percent, including Virginia (49%), Georgia (43%), Maryland (33%), and North Carolina (33%).
- In Puerto Rico, 358 of 78 municipios have rental vacancy rates under 9.2 percent.

Aggregated Commonly Used Community Resilience Indicator

The research team developed a process to aggregate the county-level data from all 20 commonly used community resilience indicators to produce a choropleth map that shows relative resilience by county. The process to create this final aggregated-data map included four steps:

1. The team oriented all of the datasets in the same direction (a higher number represents higher resilience) by reversing the data for the indicators that were negatively correlated to resilience (i.e., where higher numbers equaled less resilience).[22]
2. The research team then converted each county's data point to a standardized score value based on how many standard deviations above or below the indicator's national mean it was. For example, Laramie County in Wyoming has a standardized score value for the indicator, median *Household Income*, of approximately 1.0, which means that this county's median income of $62,879 is almost exactly one standard deviation higher than the national average median income of $48,995. For datasets where data for a specific county were missing, the mean for that indicator was used to ensure that the aggregate value for the country was not increased or reduced by the missing data. Appendix F provides the national mean for each indicator.
3. The team then averaged the 20 standardized score values for each county to create an aggregated indicator by county. Because there is no validated weighting scheme for resilience indicators, the research team did not weight individual indicators in developing the aggregated indicator.
4. Finally, the team sorted the county-level aggregated indicator into five bins (Table 3). The research team used the same color scale for the aggregated-data map (Figure 21) as for the individual indicator maps (Figure 1–Figure 20). Inclusion in the yellow bin indicates the county was far above the national average (at least 1 standard deviation above the average). The next (green) bin indicates the county fell within 1 standard deviation above the average. The lightest color blue bin indicates the county fell below, but very near the average (within 0.5 standard deviation). The next slightly deeper blue bin indicates the county fell between 0.5 and 1 standard deviation below the average, and the final deepest blue bin indicates that the county fell at least 1 standard deviation below the average.

Table 3: Color Scale for Aggregate Data Map

	+1 standard deviation or more above the average
	Above 0 but <+1.0 standard deviation above average
	Below 0, but >−0.5 standard deviation below average
	Between −0.5 and −1.0 standard deviation below average
	−1.0 standard deviation or more below the average

[22] Indicators were changed to "% population under 65," "% with HS diploma," "% without a disability," "% speaking English fluently," "% with health insurance," "% own a vehicle," "% employed." "% non-single family HH," "% housing not mobile homes," "reverse Gini index," and "population stability."

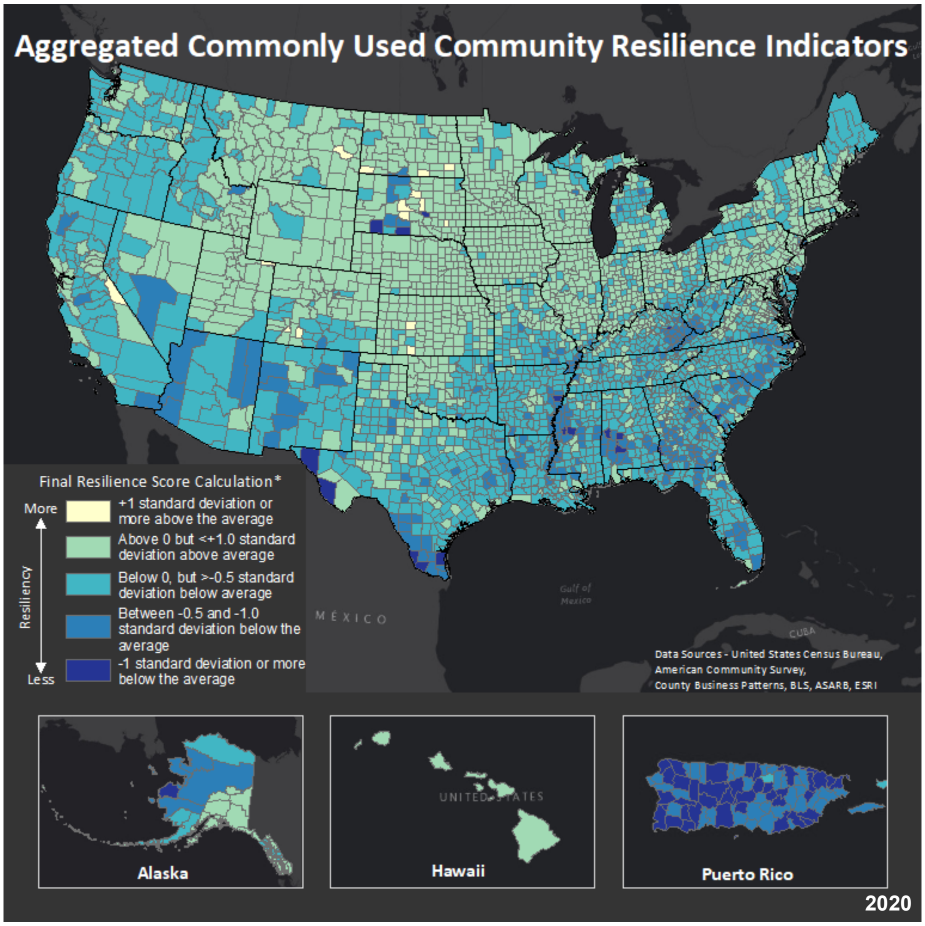

Figure 21. Aggregated Commonly Used Community Resilience Indicators

Regional Analysis of Aggregated Data

States in the Southeast: West Virginia, District of Columbia, Delaware, Maryland, Virginia, Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Florida, Alabama, Mississippi, Arkansas, and Louisiana

- Counties in southeastern states have populations with higher challenges to resilience based on indicators including lack of *Educational Attainment*, less *Household Income*, higher rates of *Single-Parent Households*, *Unemployment*, *Income Inequality*, population with a *Disability*, and lack of *Health Insurance*.
    - Some counties in Georgia, Alabama, Arkansas, Kentucky, Virginia, and Louisiana also have higher rates (greater than 10%) of households that lack *Access to a Vehicle*.
    - Several counties in the Southeast also have a higher concentration or *Presence of Mobile Homes*, making their housing more vulnerable to prevalent hazards such as flooding, hurricanes, and tornadoes.
    - Florida has counties with some of the highest rates of *Age* (i.e., adults over 65), a population with fewer years living in the location and therefore less experience of local hazards, and a few counties with populations with *Limited English Proficiency*. Florida also has lower levels of *Affiliation with a Religion,* which could make it more difficult to mobilize communities either before or after a disaster.
- Counties in the Appalachian region of Ohio, West Virginia, and Kentucky have many counties that fall into the least resilient bins for populations with lack of *Educational Attainment*, a *Disability*, and *Presence of Mobile Homes*.

States in the Southwest: Texas, Oklahoma, New Mexico, and Arizona

- Texas stands out among states in the Southwest, with many counties having populations facing relatively more challenges including: lack of *Educational Attainment* (below high school education), , and lack of *Health Insurance*. In addition, counties in the southern part of the state and on the U.S./Mexican border have populations with more *Single-Parent Households*, *Limited English Proficiency*, higher *Unemployment Rate*, and less access to health practitioners *(Medical Professional Capacity) and Health Insurance*.
- New Mexico has several counties with lower rates of resilience as related to populations with a *Disability*, lower levels of Household Income, *Unemployment Rate*, *Single-Parent Households*, and lower rates of *Medical Professional Capacity.* More than half of the counties reported that mobile homes represented 20.7 percent or more of all housing units.
- For Arizona, the counties on the eastern border with New Mexico, and the counties that border Mexico and California have populations with lower levels of *Household Income*, higher rates of *Single-Parent Households*, populations with a *Disability*, and *Age* (65 and older). These counties also have a high prevalence of mobile homes (*Presence of Mobile Homes*). Several Indian reservations lie within these counties, including the Hopi, Fort Apache, Navajo Nation, and Fort Mojave reservations.

States in the West: California, Nevada, Utah, Colorado, Wyoming, Oregon, Washington, Idaho, Montana, Alaska, and Hawaii

- The counties in the middle of and in northern California have indicators showing lower levels of resilience including lack of *Educational Attainment*, *Single-Parent Households*, and lower *Household Income*. Northern California also has higher percentages of adults age 65 and older *(Age)* and population with a *Disability*.

- Potential challenges to resilience in Oregon communities may include a high proportion of its population age 65 and older (*Age*), with lower levels of *Household Income* and living with a *Disability*. There are also relatively high numbers of *Single-Parent Households,* and individuals who live in mobile homes (*Presence of Mobile Homes*).
- Alaska, especially in the northwestern part of the state, has several counties that have lower levels of resilience including lack of *Educational Attainment* (below high school education), lower *Household Income* levels, lower owner-occupied housing units, higher *Single-Parent Households* and *Unemployment Rate*, and very low rates of *Health Insurance*. Many households are also without a vehicle *(Mobility)*.
- Although Hawaii faces challenges in hospital coverage and number of schools, overall it is relatively resilient in the context of the indicators selected for this analysis. Distance from the mainland poses unique challenges for Hawaii, however, and should be considered when evaluating each indicator.

States in the Midwest: North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Indiana, Michigan, and Ohio

- In general, counties in these states have relatively strong rates of *Educational Attainment* and *Health Insurance* coverage and lower levels of *Unemployment Rate*, *Single-Parent Households*, and populations with a *Disability*.
- A few counties in South Dakota tend to overlap with several Indian reservations, including Cheyenne River and Standing Rock. These counties face severe *Unemployment Rate*, lack of *Health Insurance*, more *Single-Parent Households*, and lower levels of *Household Income*.
- The Southeast area of Missouri that borders Arkansas, Tennessee, and Kentucky has lower levels of *Educational Attainment*, higher percentage of the population with a *Disability*, and lower presence of health-diagnosing and treating practitioners.

States in the Northeast: Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, and Pennsylvania.

- Overall, the data for counties in this area tend to be in the more resilient bins as compared to other parts of the country, with Maine as an outlier.
- Compared to the rest of the states in the Northeast, counties in Maine have higher rates of *Single-Parent Households*, lower median *Household Income*, relatively high rates of populations with a *Disability*, and more adults over 65 (*Age*).
- In New York County (Manhattan), 9.4% of the community speaks English "less than very well." New York County and Bronx County also have low rates of homeownership (20.9% and 18.6%, respectively), which, according to several of the identified research papers, is connected to resilience as both a marker of economic strength and place attachment (see Appendix C).
- With low rates of vehicle ownership, residents of New York and Bronx Counties may have more challenges evacuating. Urban counties such as these, however, are generally aware of these challenges and have addressed many of them in planning and mitigation strategies.

Puerto Rico: For every indicator where data are available, the majority of Puerto Rico's municipios are in the lower bins, except for the healthcare indicator. Puerto Rico has a unique health care program that provides services for approximately half of Puerto Rico's population.[23] Because the healthcare indicator includes both

[23] National Library of Medicine, *The Medicaid Program in Puerto Rico: Description, Context, and Trends*. Available at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4191318/, accessed September 5, 2019.

private and public healthcare, the population in Puerto Rico has relatively high rates of *Health Insurance* coverage.

National Analysis of Aggregated Data

It is important to remember that this analysis produced relative values of indicators identified from peer-reviewed research and that county-level data can mask highly challenged communities within a given county. As disasters continue to increase in frequency, all counties and communities must continue to invest in improving resilience, community functioning, and quality of life for all. Reviewing the aggregated-data map (Figure 21), this analysis suggests that those counties in the lower bins of aggregated data— that is, those counties dark and light blue on the aggregated-data map — may face multiple and interrelated challenges to resilience.[50]

Sixty-one counties with the lowest aggregated indicator values fall within the least resilient bin, which is dark blue on the Aggregated Commonly Used Community Resilience Indicators map (Figure 21). These counties are one or more standard deviations below the national average. Forty of these counties are in Puerto Rico; five in Texas; three each in Georgia, South Dakota, and Alabama, two are in Mississippi, and one is located in each of Alaska, Kentucky, South Carolina, Arkansas and New York.

A total of 309 counties fall between −0.5 and −1 standard deviation below the national average, indicating that they also may face critical challenges to disaster resilience. These counties are shaded in the medium blue on the map. Many of these counties also fall within Puerto Rico, whereas others are primarily within the Southeast and Southwest of the United States and Alaska. Taken together, the following states have 20 percent or more of their counties in one of the 2 least resilient bins: Alabama (22%), Arizona (33%), Florida (22%), Georgia (29%), Mississippi (30%), New Mexico (24.24%), South Carolina (35%), and Louisiana (20%). More than 97% of the counties in Puerto Rico are −0.5 standard deviations or greater relative to the national average.

Appendix G lists the specific counties in each of the two lower bins.

The Aggregated Commonly Used Community Resilience Indicators map highlights clusters of counties in the 2 least resilient bins that appear to be appropriate priority areas for delivery of FEMA NIC Community Resilience TA. Many of these counties are also in areas of high risk to natural hazards. These areas include:

- Central Appalachian counties in Kentucky, West Virginia, and Virginia
- The Mississippi Delta region in the states of Louisiana, Mississippi, and Arkansas
- Southwestern Alabama and counties through the Southeast
- Counties and tribal nations in south and central South Dakota
- Counties and tribal nations in New Mexico and Arizona
- South Texas
- Puerto Rico
- The western coast and interior of Alaska.

Implications for Emergency Managers

Understanding how these indicators relate to resilience has important implications for emergency managers and community leaders. Rather than attempting to influence the indicator metric (e.g., advocating for greater high school graduation rates or increasing the number of health diagnosing and treating practitioners), these indicators highlight areas where emergency managers should consider outreach strategies and emergency operations plans. Below are examples of how emergency managers can target preparedness outreach and update community response plans using this Community Resilience Indicator Analysis.

High Percentage of Single-Parent Households

The research community posits that *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. In addition, correlation analysis identifies that the indicator *Single-Parent Households* is positively correlated with higher levels of *Unemployment Rate*, and lower levels of *Educational Attainment* and *Health Insurance*. *Single-Parent Households* is negatively correlated with *Household Income* and *Home Ownership*.

- **Preparedness Outreach:** Outreach to increase preparedness and resilience for *Single-Parent Households* should focus on partnering with social service agencies, community organizations, and schools that are already serving this population, to include those associated issues of *Unemployment Rate*, lower *Household Income*, and affordable housing (*Rental Property Capacity*). For example, organizations like Supplemental Nutrition Assistance Program (SNAP), Head Start, and foodbanks currently assisting single parents can be a conduit for providing preparedness information and can help make sure these parents get needed support after a disaster. Because of the correlation with lower levels of *Educational Attainment* (below high school), outreach materials for this population should be plain language, use visual cues, and be written at the sixth-grade level.
- **Community Response Plans:** If there are geographic areas with greater numbers of *Single-Parent Households*, emergency managers should help ensure that community plans address their needs relative to evacuation transportation, sheltering, and child care.

High Presence of Mobile Homes

Communities with higher numbers of mobile homes face greater challenges to resilience because mobile homes are less secure than built housing. In addition, mobile homes are frequently found outside of metropolitan areas that may not be readily accessible by interstate highways or public transportation.

Correlation analysis identified that this indicator is positively correlated with higher levels of *Disability*, as well as lack of *Health Insurance* and *Educational Attainment*. It is negatively correlated with *Household Income* and *Medical Professional Capacity*.

- **Preparedness Outreach:** Because of the construction and lower building heights of mobile homes, they are more vulnerable to high wind or flood disasters. Mobile home residents need to pay close attention to alerts and warnings, know protective actions, and practice going to safe locations near their mobile home community. Emergency managers should work with mobile home park managers to conduct trainings and drills and to promote home or rental insurance in these communities. Outreach materials for this population should be plain language, use visual cues, and be written at the sixth-grade level.
- **Community Response Plans:** Plans that focus on the areas with higher *Presence of Mobile Homes* should also consider the higher incidence of *Disability* among this population. This group may need higher levels of evacuation support, especially to include accessible public transportation, which may not normally be accessible in these locations.

Lower Levels of Hospital Capacity per Capita and Lower Access to Medical Professional Capacity

These indicators represent essential community infrastructure for resilience, both because they represent the capacity of the healthcare system to support residents' overall health and because they provide critical emergency medical care. Lack of this critical capacity negatively effects a community's ability to respond to and recover from disasters.

- **Preparedness Outreach:** To address lower levels of *Hospital Capacity* per capita and lower access to medical practitioners (*Medical Professional Capacity*), emergency managers and community partners such as businesses, faith-based organizations, and homeowners associations can encourage community members to take first aid training or "You Are The Help until Help Arrives" training so that individuals can provide basic care in the immediate aftermath of a disaster. Preparedness campaigns should stress the importance of training and having adequate medical supplies on hand.
- **Community Response Plans:** Plans should address how to provide surge medical services by, for example, making sure their community has an active Medical Reserve Corps and Community Emergency Response Teams (CERT) Program. Emergency managers can also work with local public health agency to create mobile or pop-up medical care facilities.

Applications and Future Research

Because resilience is a latent concept (generally measurable only *after* an impact), resilience is exceptionally challenging to measure or to anticipate. FEMA NIC TA asked Argonne to examine peer-reviewed research on community resilience to identify commonly used indicators across published methodologies. By distilling the current body of research down to those indicators used in multiple methodologies, the Argonne research team has identified a manageable number of indicators to help understand factors that may have bearing on a community's resilience.

To provide a more complete picture of a community's resilience profile, FEMA developed RAPT, a user-friendly geographic information system (GIS)-based tool that includes data layers of the 20 community resilience indicators highlighted in this report; historic and forecasted hazard risk, NWS forecasts of severe weather; and infrastructure locations, including hospitals, mobile home parks, and nursing homes. This tool will help FEMA, SLTT emergency managers, and whole community partners begin to understand and improve those root community attributes that may contribute to lowered resilience when disasters occur. RAPT is available online at http://bit.ly/ResiliencePlanningTool.

As the social science of community resilience continues to evolve, additional analysis could evaluate the usefulness of weighting the indicators and examining benefits or drawbacks to adding specific risks. In addition, 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. Analysts could also conduct a comparative study to evaluate the analysis presented here with the others reviewed in the literature.

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Appendix A: Community Resilience Definitions

The Community Resilience Indicator Analysis identified eight community resilience assessment methodologies that met the inclusion criteria established for this analysis. The chart below provides those methodologies' definitions of community resilience.

Methodology/Date	Date	Definition of Community Resilience
Australian National Disaster Resilience Index (ANDRI)[a]	2017	The Australian Natural Disaster Resilience Index focuses on community resilience to natural hazards. It is based on two sets of capacities: coping capacities and adaptive capacities. ▪ Coping capacity is defined as the means by which people or organizations use available resources, skills, and opportunities to face adverse consequences that could lead to a disaster. Coping capacity captures the characteristics of a system that allow it to anticipate, act, achieve goals, and manage resources or that are associated with absorptive capacity and mobilization when a natural hazard event occurs. In a practical sense, coping capacity relates to the factors influencing the ability of a community to prepare for, absorb, and recover from a natural hazard event. ▪ Adaptive capacity differs from coping capacity in that adaptive capacity focuses on the potential for the facilitation of adaptation by governance, institutional, management, and social arrangements and processes, whereas coping capacity focuses on the capacities of communities to anticipate and respond to hazards.
Baseline Resilience Indicators for Communities (BRIC)[b]	2014	As an ideal, BRIC views inherent community disaster resilience as a complex process of interactions between various social systems, each with its own form and function but working in tandem to provide for the betterment of the whole community.
Community Disaster Resilience Index (CDRI)[c]	2010	Community, for the purposes of this work, is defined as an ecological network of social systems. A resilient system implies robustness, rapidity, and enhancement in response to natural hazards/disasters. A resilient system is, relatively speaking, robust with respect to its ability to absorb and resist the impacts of a hazard agent's potential disaster impacts. Furthermore, having experienced a disaster, a resilient system is able to bounce back quickly, reaching restoration levels in, relatively speaking, rapid fashion. Finally, as part of the recovery process, a resilient system enhances its capacities by improving its mitigation status, reducing pre-existing vulnerabilities, and improving its sustainability.
Community Resilience Index (CRI2)[d]	2010	In this theory, four sets of networked resources or capacities (Economic Development, Social Capital, Information and Communication, and Community Competence) define and shape the process of community resilience, that is, the community's ability to "bounce back" from severe stress. These adaptive capacities are not specific strategies for emergency preparedness but are a part of the social and economic fabric of the community.
Disaster Resilience of Place (DROP)[e]	2010	Resilience is a set of capacities that can be fostered through interventions and policies, which in turn help build and enhance a community's ability to respond to and recover from disasters.

Methodology/Date	Date	Definition of Community Resilience
Resilient Capacity Index (RCI)[f]	2018	The way to assess a region's resilience is by its qualities to cope with future challenges and respond effectively to future stress, a concept labeled "resilience capacity."
Social Vulnerability Index (SVI)[g]	2011	Social vulnerability refers to the socioeconomic and demographic factors that affect the resilience of communities. Vulnerability is the extent to which persons or things are likely to be affected. [Note: resilience is not further defined.]
The Composite Resilience Index (TCRI)[h]	2015	A combination of the four resilience environments (social, built, natural, and economic) presents a holistic overview of a community's resilience level. ▪ Social resilience allows individuals and communities to adapt to extreme circumstances and lessens their impact through mobility, individual-individual, and individual-community interactions. ▪ Resilience in the built environment is enhanced through the provision of emergency services, essential infrastructure, and access and evacuation potential. The natural environment encompasses flora and fauna (including humans) and their interaction with the natural landscape. The geographical location and natural features of a site have a significant impact on the vulnerability of a location. ▪ The economic environment of a community has a significant impact on its resilience. Herein, the economic environment is considered to include factors such as employment, income, productivity, wealth, and inequality.

[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 March 27, 2018.

[b] BRIC: Susan L. Cutter, Kevin D. Ash, and Christopher T. Emrich, 2014, "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*, December. 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 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] 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*, 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.

Appendix B: Community Resilience Methodologies

This table lists the 73 unique methodologies identified in the meta-analyses as described in the chapter titled "Process to Identify and Map Commonly Used Indicators of Community Resilience." The first column is the short form of the methodology name, and the second column notes which of the meta-analyses referenced that specific methodology (the methodology corresponding to the referenced number appears at the end of the table). The third column lists the date of publication. The fourth column provides the full name of the methodology and a link to more information. The remaining columns provide an assessment of the methodology for each of the inclusion criteria.

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
AGIR	3	2015	European Commission, *Global Alliance for Resilience Initiative (AGIR): Measuring and Monitoring Progress on Resilience Building for Food and Nutrition Security* http://ec.europa.eu/echo/files/policies/resilience/eu_resilience_compendium_en.pdf	Country	West Africa	Food Security	Pre	Mix	No	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
ANDRI	1	2015	Bushfire and Natural Hazards Cooperative Research Centre, *The Australian Natural Disaster Resilience Index: Annual Project Report 2014* https://www.bnhcrc.com.au/file/4862/download?token=Al2J3m1F [Must be authorized to access]	Community	Australia	Natural	Pre	Mix	Yes	Yes
ASPIRE	4	2014	The World Bank, *The Atlas of Social Protection Indicators of Resilience and Equity* http://datatopics.worldbank.org/aspire/documentation	Country	Global	Poverty	Pre	Yes	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
BCRD	1	2011	RAND *BCRD – Building Community Resilience to Disasters – A Way Forward to Enhance National Health Security* http://www.caloes.ca.gov/AccessFunctionalNeedsSite/Documents/Building%20Community%20Resilience%20to%20Disaster.pdf	Community	United States	Health	Pre	Mix	No	Mix
BRIC	1, 2, 3, 4, 5, 6	2014	Susan Cutter et al., BRIC: Baseline Resilience Indicators for Communities, *The Geographies of Community Disaster Resilience* https://www.sciencedirect.com/science/article/pii/S0959378014001459	County	United States	Multiple	Pre	Yes	Yes	Yes
CARRI	1, 6	2008	Oak Ridge National Laboratory *Community and Regional Resilience Initiative* http://www.resilientus.org/wp-content/uploads/2013/03/FINAL_CUTTER_9-25-08_1223482309.pdf	Community	United States	Multiple	Pre	Yes	Yes	Not Identified

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CART	1, 2, 4	2012	R.L. Pfefferbaum et al. Terrorism and Disaster Center, University of Oklahoma Health Sciences Center, *CART: Communities Advancing Resilience Toolkit* https://www.ncbi.nlm.nih.gov/pubmed/24180095 and https://www.oumedicine.com/docs/ad-psychiatry-workfiles/cart_online-final_042012.pdf?sfvrsn=2	Community	United States	Multiple	Pre	No	Yes	No
CCR/ IOTWS	1, 5	2007	United States Agency for International Development (USAID)-Asia Community Coastal Resilience U.S. Indian Ocean Tsunami Warning System Program, *A Guide for Evaluating Coastal Community Resilience to Tsunami/Other Hazards* https://www.crc.uri.edu/download/CCRGuide_lowres.pdf	Community	Southeast Asia	Tsunami	Pre	No	Yes	No
CCRAM	4, 5	2013	D. Leykin et al., *Conjoint Community Resilience Assessment Measure* https://www.ncbi.nlm.nih.gov/pubmed/24091563 and http://in.bgu.ac.il/en/PREPARED/Pages/ccram.aspx	Community	Global	Multiple	Pre and post	Mix	No	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CDR	1	2015	D. Keun et al., *A Measurement of Community Disaster Resilience in Korea* http://www1.cpij.or.jp/com/iac/sympo/13/ISCP2013-24.pdf	Community	South Korea	Natural	Pre	Yes	Yes	Yes
CDRI	1, 4, 5	2010	Coastal Services Center and National Oceanic and Atmospheric Administration (NOAA) Hazard Reduction and Recovery Center, Texas A&M, *Development of a Community Disaster Resilience Framework and Index* https://www.researchgate.net/profile/Walter_Peacock/publication/254862206_Final_Report_Advancing_the_Resilience_of_Coastal_Localities_10-02R/links/00b7d51feb3e3d0d4a000000.pdf	Coastal	U.S. Coastal	Multiple	Pre	Mix	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CDRI2	1, 5	2010	Kyoto University, United Nations International Strategy for Disaster Reduction (UNISDR), *CDRI2: Climate and Disaster Resilience Initiative; Capacity Building Program* http://lib.riskreductionafrica.org/bitstream/handle/123456789/625/climate%20and%20disaster%20resilience%20initiative%20capacity%20building%20program.pdf?sequence=1	City	Southeast Asia	Multiple	Pre	Mix	Yes	No
CDRST	1	2015	Torrens Resilience Institute, *Developing a Model and Tool to Measure Community Disaster Resilience* http://www.flinders.edu.au/centres-files/TRI/pdfs/trireport.pdf and http://www.emeraldinsight.com/doi/pdfplus/10.1108/IJDRBE-03-2015-0008	Community	Australia	Multiple	Pre	Mix	Yes	Mix
CERI	1	2010	Advantage West Midlands, *Community Economic Resilience Index* http://webarchive.nationalarchives.gov.uk/+/http:/www.advantagewm.co.uk/Images/Community%20Economic%20Resilience%20Index_tcm9-33264.pdf	Community	U.K.	Recession	Pre	Yes	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CoBRA	1, 3, 4	2014	United Nations Development Programme (UNDP)/Drylands Development Centre, *Community Based Resilience Analysis* http://www.undp.org/content/undp/en/home/librarypage/environment-energy/sustainable_land_management/CoBRA.html	Community	Kenya, Uganda	Drought	Pre	No	Yes	No
CRDSA	1, 5	2015	S.A. Alshehri et al., *Disaster Community Resilience Assessment Method: A Consensus based Delphi and AHP Approach* https://link.springer.com/article/10.1007%2Fs11069-015-1719-5	Community	Saudi Arabia	Multiple	Pre	Mix	No	No
CR-E	5	2015	Nasrullah et al., *Status of Community Resilience in Disaster Prone Districts of Pakistan* https://file.scirp.org/pdf/OJER_2015112714454948.pdf	District	Pakistan	Earth-quake	Pre	Yes	Yes	No
CREAT	4	2016	U.S. Environmental Protection Agency, Climate Resilience Evaluation and Awareness Tool https://www.epa.gov/crwu/creat-risk-assessment-application-water-utilities	Water utilities	United States	Climate Risk	Pre	Mix	No	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CRF	1, 4	2015	The Rockefeller Foundation, Arup, *City Resilience Framework and City Resilience Index* https://assets.rockefellerfoundation.org/app/uploads/20140410162455/City-Resilience-Framework-2015.pdf	City	Global	Multiple	Pre	No	Yes	No
CRI	1, 2, 4	2010	Mississippi-Alabama Sea Grant Consortium, *Coastal Resilience Index: A Community Self-Assessment* http://www.southernclimate.org/documents/Coastal_Resilience_Index_Sea_Grant.pdf	Community	United States – Coastal	Coastal Hazards	Post	No	Yes	No
CRI2	1, 4	2010	K. Sherrieb et al., *Measuring Capacities for Community Resilience* (Community Resilience Index) https://link.springer.com/article/10.1007%2Fs11205-010-9576-9	County	United States	Multiple	Pre	Yes	No	Yes
CRM	1	2000	Canadian Center for Community Renewal, *The Community Resilience Manual* https://communityrenewal.ca/sites/all/files/resource/P200_0.pdf	Community	Canada and United States – Rural	Recession	Pre	Mix	Yes	No
CRR	3	2013	World Economic Forum, *Global Risks 2013* http://www3.weforum.org/docs/WEF_GlobalRisks_Report_2013.pdf	Country	Global	Multiple	Pre	Yes	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
CRS	1, 2, 4	2014	Community and Regional Resilience Institute, Meridien, *A Practical Approach to Building Resilience; Community Resilience System* http://journals.sagepub.com/doi/pdf/10.1177/0002764214550296	Community	United States	Multiple	Pre	Yes	No	No
CRT	1	2009	Bay Localize, *Community Resilience Toolkit: Workshop Guide* http://www.baylocalize.org/files/Community_Resilience_Toolkit_v1.0.pdf	City or County	United States	Climate Change	Pre	No	Yes	No
CV	6	2013	Texas A&M University, Hazard Reduction and Recovery Center, *Status and Trends of Coastal Vulnerability to Natural Hazards Project* http://www.glo.texas.gov/coastal-grants/_documents/grant-project/11-025-final-report.pdf	County	United States	Coastal Hazards	Pre	Yes	Yes	Yes (TX)
DFID	1, 4	2009	DFID Disaster Risk Reduction Interagency Coordination Group, *Characteristics of a Disaster-Resilient Community* http://discovery.ucl.ac.uk/1346086/1/1346086.pdf	Community	Global	Multiple	Pre	Mix	Yes	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
DRLA	3	2012	Disaster Resilience Leadership Academy, Tulane University, *Haiti Humanitarian Assistance Evaluation: Resilience Perspective* https://reliefweb.int/sites/reliefweb.int/files/resources/UEH%20Tulane%20DRLA%20Haiti%20Humanitarian%20Aid%20Evaluation%20ENGLISH%20May%202012.pdf	Household	Haiti	Natural	Pre	Mix	Yes	No
DROP	6	2010	S. Cutter et al., Disaster Resilience of Place, *Disaster Resilience Indicators for Benchmarking Baseline Conditions* http://resiliencesystem.com/sites/default/files/Cutter_jhsem.2010.7.1.1732.pdf	County	United States – Southeast	None	Pre	Yes	Yes	Yes
FAO	3	2010	Food and Agriculture Organization of the United Nations (UN), *FAO Resilience Tool* http://www.fao.org/docrep/013/al920e/al920e00.pdf	Community	Global	Food Security	Pre	Yes	Yes	Yes
FAO-Livelihoods	4	2010	L. Alinovi et al., European Report on Development, *Livelihoods Strategy and Household Resilience to Food Insecurity* http://www.technicalconsortium.org/wp-content/uploads/2014/05/Livelihoods-Strategies_Household-Res.pdf	Country	Kenya	Food Security	Pre	Yes	Yes	HH surveys

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
FCR	1	2014	International Federation of Red Cross, *IFRC Framework for Community Resilience* http://www.ifrc.org/Global/Documents/Secretariat/201501/1284000-Framework%20for%20Community%20Resilience-EN-LR.pdf	Community	Global	Multiple	Pre	Mix	Yes	No
FSRI	4	2015	New Economics Foundation, *Financial System Resilience Index* http://neweconomics.org/2015/06/financial-system-resilience-index/	Country	Global	Financial System	Pre	Yes	No	No
GFM	3		UN Office for the Coordination of Humanitarian Affairs (OCHA) and Maplecroft, *Global Focus Model* https://interagencystandingcommittee.org/system/files/legacy_files/Maplecroft_GFM_050412.pdf	Country	Global	Multiple	Pre	Yes	No	Mix
GRI	4	2017	FM Global, *2018 FM Global Resilience Index* https://www.fmglobal.com/research-and-resources/tools-and-resources/resilienceindex	Country	Global	Multiple	Pre	Yes	Yes	No
Grosvenor	1	2014	Grosvenor, *Resilient Cities Research Report* http://www.grosvenor.com/news-views-research/research/2014/resilient%20cities%20research%20report/	City	Global	Multiple	Pre	Mix	No	N/A

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
Hazus	2		Federal Emergency Management Agency, Hazus Methodology https://www.fema.gov/hazus	Community	United States	Earth-quake, Flood, Hurri-cane, Tsunami	Post (models' losses)	Yes	Yes	Yes
Hyogo	1, 3	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* http://www.unisdr.org/files/2259_IndicatorsofProgressHFA.pdf	City	Global	Natural	Pre and post	Mix	Yes	No
ICBRR	1, 5	2012	Canadian Red Cross, *Measuring Disaster-Resilient Communities; Integrated Community Based Risk Reduction* https://www.ncbi.nlm.nih.gov/pubmed/22576136	Coastal Community	Indonesia	Coastal Hazards	Pre	Mix	No	No
IDRI	3	2013	United Nations Development Programme, *Indonesia Disaster Recovery Index* http://www.id.undp.org/content/indonesia/en/home/presscenter/pressreleases/2013/11/27/launching-of-the-world-s-first-disaster-recovery-index.html	Community	Indonesia	Volcano/ Flood	Post	Mix	No	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
IDS	3	2013	Institute of Development Studies, *Towards a Quantifiable Measure of Resilience* https://opendocs.ids.ac.uk/opendocs/bitstream/handle/123456789/2990/Wp434.pdf;jsessionid=FF9965C00C8A54822E41F9CCE56A5974?sequence=1	Multi-level	Global	Food Security	Pre	Yes	Yes	N/A
LCOT	3	2012	Tufts University, *Livelihoods Change Over Time* http://fic.tufts.edu/research-item/livelihoods-change-over-time/	Household	Sudan, Ethiopia, Haiti	Multiple	Post	Yes	Yes	Yes
LDRI	1	2013	P.M. Orencio and M. Fujii, Localized Disaster-Resilience Index http://www.sciencedirect.com/science/article/pii/S2212420912000428?via%3Dihub	Community	Philip-pines	Coastal Hazards	Pre	Mix	No	No
MCEER R4	3	2007	Multidisciplinary Center for Earthquake Engineering Research (MCEER), University of Buffalo, *Conceptualizing and Measuring Resilience* http://onlinepubs.trb.org/onlinepubs/trnews/trnews250_p14-17.pdf	Community	Global	Infra-structure	Pre	N/A	Yes	N/A

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
NIST	1, 4	2016	National Institute of Standards and Technology (NIST), *Community Resilience Planning Guide for Building and Infrastructure Systems* (Volumes 1 and 2) https://www.nist.gov/topics/community-resilience/planning-guide	Community	Kenya/ Uganda	Infra-structure	Pre	No	Yes	No
ODI	3	2013	Overseas Development Institute, *Disaster Risk Management Potential Targets and Indicators* http://www20.iadb.org/intal/catalogo/PE/2013/11856.pdf	Community	Global	Multiple	Both	Yes	No	N/A
ORP	2	2013	Oregon Seismic Safety Policy Advisory Commission, *The Oregon Resilience Plan Reducing Risk and Improving Recovery for the Next Cascadia Earthquake and Tsunami* http://www.oregon.gov/oem/Documents/Oregon_Resilience_Plan_Final.pdf	Regional	Oregon	Infra-structure	Post	Mix	Yes	No
OXFAM	4	2013	OXFAM, *A Multidimensional Approach to Measuring Resilience* https://policy-practice.oxfam.org.uk/publications/a-multidimensional-approach-to-measuring-resilience-302641	Community	Global	Humani-tarian	Pre	Mix	No	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
PEOP-LES	1, 3, 4, 5	2010	NIST, MCEER: University of Buffalo, *PEOPLES Resilience Framework* http://peoplesresilience.org/wp-content/uploads/2013/07/2010_Renschler_PEOPLES_Resilience.pdf	Community	United States	Multiple	Pre	Mix	No	Yes
PVI	3	2011	Inter-American Development Bank, *Indicators of Disaster Risk and Risk Management; Prevalent Vulnerability Index* https://publications.iadb.org/handle/11319/5237	Country and Subnational	Latin America	Multiple	Pre	Yes	No	Yes
RASA	6	2008	B. Maguire and S. Cartwright, *Assessing a Community's Capacity to Manage Change: A Resilience Approach to Social Assessment* http://www.tba.co.nz/tba-eq/Resilience_approach.pdf	Community	Australia (rural)	Water Scarcity	Pre	No	Yes	No
RCI	3		Research Network on Building Resilient Regions, *Resilience Capacity Index* https://www.macfound.org/networks/research-network-on-building-resilient-regions/details/	Metropol-itan Statis-tical Area	United States	Multiple	Pre	Yes	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
RCI2 – Regions	4	2008	Berkeley Institute of Urban and Regional Development, *Resilience and Regions: Building Understanding of the Metaphor* https://iurd.berkeley.edu/wp/2007-12.pdf	Metro Regions	Global	Multiple	Pre	N/A	Yes	N/A
RELi	1	2015	Capital Markets Partnership, *RELi Resilience Action Checklist* http://online.anyflip.com/zyqc/ojoi/mobile/index.html#p=14	Community	United States	Infra-structure	Pre	No	Yes	No
ResilUS	1, 3, 4, 6	2011	U.S. Resilience Institute, Western Washington University, *ResilUS* https://huxley.wwu.edu/ri/resilus	Community	United States	Earth-quake	Post	Yes	No	Yes
RIM	6	2016	N.S. Lam et al., Resilience Inference Measurement: Measuring Community Resilience to Coastal Hazards along the Northern Gulf of Mexico https://www.ncbi.nlm.nih.gov/pubmed/27499707	County	United States	Coastal Hazards	Post	Yes	Yes	Yes
RMI	4	2013	Argonne National Laboratory, *Resilience Measurement Index: Indicator of Critical Infrastructure Resilience* http://www.ipd.anl.gov/anlpubs/2013/07/76797.pdf	Facility	United States	Infra-structure	Pre	Mix	No	Mix

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
RRI	3	2013	DARA, *Risk Reduction Index* http://daraint.org/wp-content/uploads/2012/01/How_does_the_RRI_work.pdf	Territorial Units	West Africa	Multiple	Pre	No	Yes	No
RRI – Rural	1	2014	Rural Disaster Resilience Project, *Rural Resilience Index* http://journals.sagepub.com/doi/pdf/10.1177/0002764214550297	Community – Rural	Global	Multiple	Pre	No	No	N/A
SERI	3	2013	Verisk Maplecroft, Socio-economic Risk Index https://www.maplecroft.com/human-rights-political-environmental-economic-risk-indices	Country	Global	Multiple	Pre	Yes	No	N/A
SPUR	1, 2, 4, 6	2009	San Francisco Planning + Urban Research Association, *The Resilient City: Defining What San Francisco Needs From Its Seismic Mitigation Policies* https://www.spur.org/sites/default/files/publications_pdfs/SPUR_Seismic_Mitigation_Policies.pdf	Community	United States	Earth-quake/ Infra-structure	Post	Yes	No	No
Surging Seas	4	2013	Climate Central, Surging Seas Risk Finder https://riskfinder.climatecentral.org/	Community	U.S. Coast	Storm Surge/ Flood	Pre	Yes	Yes	Yes
SVI	7	2011	Agency for Toxic Substances & Disease Registry, *Social Vulnerability Index* https://svi.cdc.gov/	County	United States	Multiple	Pre	Yes	Yes	Yes

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
TCRI	1	2015	T. Perfrement and T. Lloyd, *The Composite Resilience Index* https://www.myresilient.city/concepts/17-composite-resilience-index-2.html	Community	Australia	Natural	Pre	Yes	Yes	Yes
THRIVE	1	2004	Prevention Institute, *THRIVE Tool for Health & Resilience in Vulnerable Environments* https://www.preventioninstitute.org/tools/thrive-tool-health-resilience-vulnerable-environments	Community	United States	Health Disparity	Pre	Mix	Yes	No
TNC Coastal Resil-ience	4	2015	The Nature Conservancy, *Coastal Resilience Mapping Tool* https://maps.coastalresilience.org/	Community	Global	Coastal Hazards	Pre	Yes	No	Yes
TRIAMS	3	2006	World Health Organization, *Tsunami Recovery Impact Assessment and Monitoring System Risk Reduction Indicators* http://www.who.int/hac/crises/international/asia_tsunami/triams/risk_reduction_indicators_pro_vention.pdf?ua=1	Community	Indian Ocean	Tsunami	Post	Mix	Yes	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
UCR	1	2014	Rockefeller Foundation, *Urban Climate Resilience: A Review of Methodologies Adopted under the ACCCRN Initiative in Indian Cities* https://www.researchgate.net/publication/275521843_Urban_Climate_Resilience_A_review_of_the_methodologies_adopted_under_the_ACCCRN_initiative_in_Indian_cities	City	India	Natural	Pre	No	No	No
UDRI	1	2015	Earthquakes and Megacities Initiative, *A Guide to Measuring Urban Risk Resilience – the Urban Disaster Risk Index (UDRI)* https://www.cedim.de/download/Guidebook_URR_ME-July-2015.pdf	City	Global	Natural	Post	Mix	Yes	No
UNISDR	1, 2, 4	2014	UNISDR, *Disaster Resilience Scorecard for Cities* http://www.unisdr.org/we/inform/publications/53349	City	Global	Multiple	Pre	No	Yes	No

Name	Meta-analysis Sources*	Date Pub-lished	Developer/Title/Links	Unit of Analysis	Area of Focus	Risk Focus	Pre or Post Dis-aster	Quanti-tative?	Public Do-main?	Public Data Source?
USAID	1, 4	2013	Feed the Future, *Community Resilience: Conceptual Framework and Measurement – Feed the Future Learning Agenda* https://agrilinks.org/sites/default/files/resource/files/FTF%20Learning_Agenda_Community_Resilience_Oct%202013.pdf	Community	Global	Poverty	Pre	Yes	No	No
WISC	6	2014	WISC: Well-being, Identity, Services and Capitals *Theorizing Community Resilience to Improve Computational Modeling* https://ascelibrary.org/doi/pdf/10.1061/9780784413609.265	Community	United States	Multiple	Pre	Yes	No	Yes
WRI	3	2016	Institute for Environment and Human Security of the United Nations, *World Risk Index* http://www.irdrinternational.org/2016/03/01/word-risk-index/	Country	Global	Multiple	Pre	Yes	Yes	Yes

*Meta-analysis key:

1. Ayyoob Sharifi, 2016, "A Critical Review of Selected Tools for Assessing Community Resilience," *Ecological Indicators* 69: 629–647. Available at http://dx.doi.org/10.1016/j.ecolind.2016.05.023, accessed April 6, 2018.
2. Francis M. Lavelle, Liesel A. Ritchie, Alexis Kwasinski, and Brian Wolshon, 2015, "Critical Assessment of Existing Methodologies for Measuring or Representing Community Resilience of Social and Physical Systems," *NIST GCR 15-1010*. Available at 2018. http://dx.doi.org/10.6028/NIST.GCR.15-1010, accessed April 6, 2018.

3. Thomas Winderl, 2014, "Disaster Resilience Measurements: Stocktaking of Ongoing Efforts in Developing Systems for Measuring Resilience," *United Nations Development Programme*. 2014. Available at https://www.preventionweb.net/files/37916_disasterresiliencemeasurementsundpt.pdf, accessed April 6, 2018.
4. Susan L. Cutter, 2015, "The Landscape of Disaster Resilience Indicators in the USA," *Natural Hazards* 80: 741–758. Available at http://dx.doi.org/10.1007/s11069-015-1993-2, accessed April 6, 2018.
5. Abbas Ostadtaghizadeh, Ali Ardalan, Douglas Paton, Jossain Jabbari, and Hamid Reza Khankeh, 2015, "Community Disaster Resilience: A Systematic Review on Assessment Models and Tools," *PLoS Currents*. Available at http://dx.doi.org/10.1371/currents.dis.f224ef8efbdfcf1d508dd0de4d8210ed, accessed April 6, 2018.
6. Maria Koliou, John W. van de Lindt, Therese P. McAllister, Bruce R. Ellingwood, Maria Dillard, and Harvey Cutler, 2017, "State of the Research in Community Resilience: Progress and Challenges," *Sustainable and Resilient Infrastructure*: 1–21. Available at http://dx.doi.org/10.1080/23789689.2017, accessed April 6, 2018.
7. Other methodologies identified outside of meta-analyses.

Appendix C: Commonly Used Community Resilience Indicators

In the charts that follow, reference notes (lowercase letters) in the Connection to Resilience sections indicate which methodology provided the explanation cited for why the indicator is an effective measure of community resilience. A key for the references (*a* through *h*) follows at the end of this appendix.

Population Indicators

<table>
<tr><th colspan="9">Educational Attainment – Lack of High School Diploma:
Census Tract and County Data</th></tr>
<tr><td colspan="4">Metric</td><td colspan="5">Data Source</td></tr>
<tr><td colspan="4">Percentage of population over age 25 without a high school diploma (including GED)</td><td colspan="5">U.S. Census American Community Survey (ACS) 2014–2018 five-year estimates, Table S1501</td></tr>
<tr><td colspan="4">National Average</td><td colspan="5">Binning Method</td></tr>
<tr><td colspan="4">12.3% over age 25 without a high school diploma</td><td colspan="5">County: Jenks Caspall</td></tr>
<tr><td colspan="9">Community Resilience Methodologies</td></tr>
<tr><td># of 8</td><td>ANDRI[24]</td><td>BRIC</td><td>CDRI</td><td>CRI2</td><td>DROP</td><td>RCI</td><td>SVI</td><td>TCRI</td></tr>
<tr><td>7</td><td>X</td><td>X</td><td>X</td><td>X</td><td>X</td><td>X</td><td>X</td><td></td></tr>
<tr><td colspan="9">Connection to Resilience</td></tr>
<tr><td colspan="9">Higher levels of education are associated with health, as well as an improved ability to communicate and comprehend information.[b,g]</td></tr>
<tr><td colspan="9">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]</td></tr>
<tr><td colspan="9">Higher levels of education can improve the capacity to prepare for, and respond to, the stress of disasters.[a,e,h]</td></tr>
<tr><td colspan="9">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]</td></tr>
</table>

[24] ANDRI = Australian National Disaster Resilience Index; BRIC = Baseline Resilience Indicators for Communities; CDRI = Community Disaster Resilience Index; CRI2 = Community Resilience Index; DROP = Disaster Resilience of Place; RCI = Resilient Capacity Index; SVI = Social Vulnerability Index; TCRI = The Composite Resilience Index.

Unemployment Rate: Census Tract and County Data								
Metric				Data Source				
Percentage of the labor force unemployed				ACS 2014–2018 five-year estimates, Table S2301				
National Average				Binning Method				
5.9% unemployment rate				County: Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
7	X	X	X	X	X		X	X
Connection to Resilience								
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]								

Disability: Census Tract and County Data								
Metric				Data Source				
Percentage of the population with disabilities[25]				ACS 2014–2018 five-year estimates, Table S1810				
National Average				Binning Method				
12.6% with a disability				County: Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
6	X	X			X	X	X	X
Connection to Resilience								
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]								

[25] Per the American Community Survey (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.

Limited English Language Proficiency: Census Tract and County Data

Metric	Data Source
Percentage of limited English-speaking households[26]	ACS 2014–2018 five-year estimates, Table S1602
National Average	**Binning Method**
4.4% limited English-speaking households	County: Fisher Jenks

Community Resilience Methodologies

# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
6	X	X	X		X		X	X

Connection to Resilience
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]

Home Ownership: Census Tract and County-Level Data

Metric	Data Source
Percentage of owner-occupied housing units	ACS 2014–2018 five-year estimates, Table DP04
National Average	**Binning Method**
63.8% of housing units are owner-occupied	County: Jenks Caspall

Community Resilience Methodologies

# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
6	X	X	X		X	X		X

Connection to Resilience
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]

[26] 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).

Mobility – Lack of Vehicle: Census Tract and County Data								
Metric				Data Source				
Percentage of occupied housing units with no vehicles available				ACS 2014–2018 five-year estimates, Table B08201				
National Average				Binning Method				
8.7% of households are without a vehicle				County: Head Tail Breaks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
6	X	X	X		X		X	X
Connection to Resilience								
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]								

Age 65 and Older: Census Tract and County Data								
Metric				Data Source				
Percentage of the population 65 years and older				ACS 2014–2018 five-year estimates, Table S0101				
National Average				Binning Method				
15.2% of population 65 years and older				County: Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
5	X	X			X		X	X
Connection to Resilience								
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.[g]								

Household Income: Census Tract and County Data

Metric	Data Source
Median household income	ACS 2014–2018 five-year estimates, Table S1903
National Average	**Binning Methods**
$60,273	County: Manual

Community Resilience Methodologies

# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
5	X		X	X			X	X

Connection to Resilience

Research has shown that 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]

Income Inequality: County Data

Metric	Data Source
Gini Index[27]	ACS 2014–2018 five-year estimates, Table B19083
National Average	**Binning Method**
.48	Jenks Caspall

Community Resilience Methodologies

# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4		X		X	X	X		

Connection to Resilience

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]

In addition, a skewed distribution of economic resources may negatively affect the cohesiveness of the residents' response to a disaster.[f]

[27] 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.[g] The closer the number is to 1, the greater the income inequality.

Lack of Health Insurance: Census Tract and County Data								
Metric				Data Source				
Percentage of the population without health insurance coverage				ACS 2014–2018 five-year estimates, Table S2701				
National Average				Binning Method				
9.4% without health insurance				County: Fisher Jenks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4		X	X		X	X		
Connection to Resilience								
Health is a critical component of community well-being as 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]								

Single-Parent Households: Census Tract and County Data								
Metric				Data Source				
Percentage of single-parent households				ACS 2014–2018 five-year estimates, Table DP02				
National Average				Binning Method				
32.1% of family households are single-parent				County: Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
3	X			X			X	
Connection to Resilience								
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]								

Connection to Civic and Social Organizations: County Data								
Metric				Data Source				
Number of civic and social organizations per 10,000 people				U.S. Census Bureau, 2016 County Business Patterns[28], Table 00A1, NAICS Code 8134				
National Average				Binning Method				
.83 civic and social organizations per 10,000 people				Head Tail Breaks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
6		X	X	X	X	X		X
Connection to Resilience								
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]								

Hospital Capacity: County Data								
Metric				Data Source				
The number of hospitals per 10,000 people				U.S. Census Bureau, 2016 County Business Patterns[28], Table 00A1, NAICS code 622110				
National Average				Binning Method				
.17 hospitals per 10,000 people				Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
5	X	X	X		X			X
Connection to Resilience								
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]								

[28] While U.S. Census County Business Patterns (CBP) has 2017 data, the dataset has significantly fewer records available and therefore this update will continue to use the CBP 2016 dataset in order to provide the most comprehensive data possible.

Medical Professional Capacity: County Data								
Metric				Data Source				
The number of health-diagnosing and treating practitioners per 1,000 population				ACS 2014–2018 five-year estimates, Table S2401				
National Average				Binning Method				
19 health diagnosing and treating practitioners per 1,000 population				Fisher Jenks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
5	X	X	X	X	X			
Connection to Resilience								
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]								

Affiliation with a Religion: County Data								
Metric				Data Source				
Percentage of the population that are religious adherents				Association of Statisticians of American Religious Bodies. 2010 U.S. Religion Census. http://www.usreligioncensus.org/index.php				
National Average				Binning Method				
51.4% of the population are religious adherents				Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4		X	X	X	X			
Connection to Resilience								
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]								

Presence of Mobile Homes: Census Tract and County Data								
Metric				Data Source				
Percentage of mobile homes				ACS 2014–2018 five-year estimates, Table DP04				
National Average				Binning Method				
6.2% of housing units are mobile homes				County: Fisher Jenks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4	X	X			X		X	
Connection to Resilience								
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.[g]								

Public School Capacity: County Data								
Metric				Data Source				
The number of public schools per 5,000 population				U.S. Department of Education. National Center for Education Statistics. Elementary/Secondary Information System. 2017-2018 school year. https://nces.ed.gov/ccd/elsi/				
National Average				Binning Method				
1.6 schools per 5,000 population				Head Tail Breaks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4		X	X		X			X
Connection to Resilience								
Public schools are a measure of response and recovery capacity, as they represent the community's ability to provide safe shelter for individuals and facilitate evacuations.[b,c,e,h]								
More availability of schools can increase the ability to maintain schooling after a disaster.[b]								

Population Change: County Data								
Metric				Data Source				
The net migration (international and domestic) of individuals.				U.S. Census Bureau, Population Division. Table: Cumulative Estimate of the Components of Resident Population Change (PEPTCOMP): April 1, 2017 to July 1, 2018				
National Average				Binning Method				
On average, county populations have grown by 643 people from July 2017 to July 2018				Jenks Caspall				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
4	X	X		X		X		
Connection to Resilience								
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]								

Hotel/Motel Capacity: County Data								
Metric				Data Source				
The number of hotels/motels/casinos per 5,000 population				U.S. Census Bureau, 2016 County Business Patterns[28], Table 00A1, NAICS Codes 72111 and 721120				
National Average				Binning Method				
.83 hotels/motels/casinos per 5,000 population				Head Tail Breaks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
3		X	X			X		
Connection to Resilience								
Hotels and motels can provide important capacity to house individuals who have to leave their homes, either to find safe shelter from the disaster or as temporary housing during the recovery phase.[b,e]								
Fewer local hotels and motels may mean that individuals have to leave an area, making recovery from a disaster more difficult.[a]								

Rental Property Capacity: Census Tract and County Data								
Metric				Data Source				
Rental Vacancy Rate of Total Housing Units				ACS 2014–2018 five-year estimates, Table DP04[29]				
National Average				Binning Method				
6% rental vacancy rate				County: Fisher Jenks				
Community Resilience Methodologies								
# of 8	ANDRI	BRIC	CDRI	CRI2	DROP	RCI	SVI	TCRI
3		X	X		X			
Connection to Resilience								
While low numbers of vacant housing units may seem to be a positive indicator of economic resilience, it does denote a lack of physical capacity to house individuals who have been displaced by a disaster.[b,e]								
A greater presence of vacant housing units provides immediately available housing stock so residents do not need to leave their communities because of a lack of housing stock.[b,e]								

Key:

[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, "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*, December. 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 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] 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*, 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.

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Appendix D: Binning Methodology

The Python Spatial Analysis library, PySAL, is an open source collection of spatial analysis functions written in Python intended to support the development of high-level applications.[30] The sub-package Exploratory Spatial Data Analysis (ESDA) contains a module dedicated to choropleth map classification that features several of the most often used classification methods available to the field. The research team reviewed nine of the methods (Natural Breaks, Fisher-Jenks Breaks, Jenks-Caspall Breaks, Head/Tail Breaks, Maximum Breaks, Natural Breaks, Quantiles, Equal Intervals, Percentiles, and Standard Deviation from The Mean – or "Z" Score) to determine which method for binning counties would provide the most mathematically appropriate distribution across five bins for each indicator.

The following documentation describes each method in detail, but it is worth identifying the distinction of three variations of a similar method. Please see method descriptions for further information. Three of the methods available are derived from the work of George Jenks. Each method seeks to return class breaks such that within-class differences are minimized and differences between classes are maximized.[31] However, each method approaches that goal in a unique manner.

Jenks Natural Breaks, or Natural Breaks, was originally intended to find natural shifts in histograms. The ESDA library uses a K-Means clustering algorithm to represent the natural grouping in data. K-means clustering, picks 'centers' to groups of data (typically with a random initial configuration), assigns each data point to its closest center based on Euclidean distance, picks new centers that are equal to current groups' means, and repeats until groups are stable (the module's code has a default stop at 300 iterations). Due to the random initial configuration, results are not guaranteed to be optimal or repeatable.

Fisher-Jenks Breaks optimizes squared deviations from within class means.

Jenks-Caspall Breaks optimizes absolute deviation from within class medians.

"Best fit" Classification Evaluation Methods

The map classification module includes three tools to determine the "best fit" of the several methods available.

Absolute Deviation around Class Median (ADCM): $\sum |y_c - y_{c,med}|\ for\ all\ classes, c$

Total sum of squares over all class means (TSS): $\sum (y_c - \bar{y}_c)^2\ for\ all\ classes, c$

Goodness of Absolute Deviation of Fit (GADF): compares ADCM against the absolute deviation from the median of the entire data set, $1 - \frac{\sum |y_c - y_{c,med}|\ for\ all\ classes, c}{\sum |y_i - y_{med}|\ for\ all\ data, i}$

The research team chose not to include the GADF method as this is a second measure based on deviation from the median of the data. The Jenks-Caspall method minimizes deviation from class medians, and thus its results would be over-weighted by two of three goodness-of-fit tests focusing on medians.

The team centered and scaled the evaluation results for each evaluation method so that evaluation results could be compared as similar values. The team found the average of the ADCM and TSS scores (one value to

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30 PySAL, "Spatial Analysis Library." Available at https://pysal.readthedocs.io/en/v1.11.0/library/index.html, accessed August 21, 2019.

31 PySAL, "Source code for pysal.esda.mapclassify." Available at https://pysal.readthedocs.io/en/v1.11.0/_modules/pysal/esda/mapclassify.html#quantile, accessed August 21, 2019.

represent absolute error against the median, and the second for squared error against the mean) and selected the lowest averaged score as the best method. To center a variable, the average value is subtracted from all values (the adjusted data has a mean of zero). Each value is divided by the standard deviation of the dataset so that the resulting dataset has a common standard deviation of one (the data have been centered and scaled).

Natural Breaks

Natural Breaks, or Jenks Natural Breaks, is a method that groups data according to natural groupings in the data values, minimizing differences between data values in the same class and maximizing differences between different classes.[32] It is a subjective method that works best with clustered datasets.

Fisher–Jenks Breaks

The 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

The 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[33] works well with heavily tailed datasets, iterating through the data to minimize around the mean. The Head/Tail Breaks method groups the data values into two parts around the arithmetic mean and iteratively partitions until there are fewer higher values. Along the number line, the head represents the values above the mean and the tail below. For a simple implementation of the Head/Tail Breaks classification, take all of the values and calculate the mean. Removing the values below the calculated mean, repeat the process on the larger values, calculating a new mean. Repeat this process until there are fewer data values larger than the mean than there are data values smaller than the mean within that iteration.

Maximum Breaks

Breaks are placed at the largest intervals between adjacent data values. This is an easy-to-understand method that works best with piecewise datasets with gaps. This method does not work well with skewed data. To implement, the data values are ordered from low to high, and the difference between sequential data values are calculated. Breaks are placed where the differences are the largest, and the number of breaks is based on the number of classes desired.

Standard Mean

The method groups data values according to the distance to the mean standard deviation of the dataset. Using this method, the mean and standard deviation are taken from the dataset holistically, and the standard deviation from the mean is used to determine into which class each data value falls. This method is useful for normally distributed datasets in which classifying data as "above average" or "below average" makes a meaningful break in the data. This method does not work well with heavily skewed or non-normally distributed data. Mean-Standard Deviation classification is implemented by calculating the mean value of the dataset and the standard deviation, placing class breaks at the mean value and each standard deviation value.

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[32] T. A. Slocum, R. B. McMaster, F. C. Kessler, and H. H. Howard, 2009, *Thematic Cartography and Geovisualization,* 3rd ed. Upper Saddle River, NJ: Pearson Prentice Hall.;
B. D. Dent, J. S. Torguson, and T. W. Hodler, 2008, *Cartography: Thematic Map Design*, 6th Edition. McGraw-Hill.

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

Quantiles

Equal numbers of data observations are placed into each category. Data are classified into groups like Top 20%, Upper-Middle 20%, Middle 20%, Lower-Middle 20%, and Bottom 20%. This method is easy for the map reader to understand. Because there are equal numbers of observations in each class, the map will always produce distinguishable patterns.

Percentiles

Data are classified into groups at 1%, 10%, 50%, 90%, 99%, and 100%. This method is structured similar to quantiles and is useful to highlight the extremes of a data set.

Equal Interval

Each class breaks at regular intervals along the number line at a set equivalent range. These breaks might be 20, 30, 40, etc., where each class is used to represent an equivalent range of measured data values. Classes are chosen regardless of the data. The Equal Interval method is easy to read and understand; however, it can be misleading in that no information is given on the distribution of the data within each distinct class. Method is calculated by taking the highest data value minus the lowest data value and dividing by the number of classes desired to get class breaks at equivalent intervals.

Other

In a specific case the team used an alternative criteria to select a binning methodology. For Median Household Income, a convention for displaying income data already exists: $0–20,000, $20,001–$40,000, etc. (an intuitive methodology that is similar to equal intervals).

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Appendix E: Indicator Correlation Table

The research team conducted a correlation analysis to measure and describe the strength and direction of the relationships among the 20 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 Coefficient 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 E-1 summarizes some highlights of the correlation analysis.

Table E- 1: Highlighted Correlation Relationships

Indicator	Positively Correlates With	Negatively Correlates With
Age (adults over 65)	• Disability (r = 0.41)	• Population Change (r = -0.34) • Single-Parent Households (r = -0.31).
Lack of High School Diploma	• Single-Parent Household (r = 0.53) • Unemployment Rate (r = 0.50) • Lack of Health Insurance (r = 0.46) • Presence of Mobile Homes (r = 0.45) • Population with a Disability (r = 0.43) • Limited English Language Proficiency (r = 0.43) • Income Inequality (r = 0.37)	• Household Income (r = -0.59) • Medical Professional Capacity (r = -0.49) (access to healthcare)
Disability	• Presence of Mobile Homes (r = 0.48) • Lack of High School Diploma (r = 0.43) • Unemployment Rate (r = 0.41) • Age (r = 0.41)	• Household Income (r = -0.66) • Medical Professional Capacity (r = -0.34) (access to healthcare)
Limited English Language Proficiency	• Unemployment Rate (r = 0.52) • Lack of High School Diploma (r = 0.43) • Lack of Vehicle (r = 0.33)	• Household Income (r = -0.31)
Lack of Health Insurance	• Lack of High School Diploma (r = 0.46) • Presence of Mobile Homes (r = 0.37)	• Medical Professional Capacity (r = -0.41) (access to healthcare)
Lack of Vehicle	• Single-Parent Households (r = 0.59) • Unemployment Rate (r = 0.50) • Income Inequality (r = 0.39) • Lack of High School Diploma (r = 0.34) • Limited English Language Proficiency (r = 0.33)	• Home Ownership (r = -0.32) • Household Income (r = -0.30)
Unemployment Rate	• Single-Parent Households (r = 0.66) • Limited English Language Proficiency (r = 0.52) • Lack of High School Diploma (r = 0.50) • Lack of Vehicle (r = 0.50) • Disability (r = 0.41)	• Household Income (r = -0.50)
Single-Parent Household (of all family households)	• Unemployment Rates (r = 0.66) • Lack of Vehicle (r = 0.59) • Lack of High School Diploma (r = 0.53) • Income Inequality (r = 0.49)	• Household Income (r = -0.48) • Age (r = -0.31)
Presence of Mobile Homes	• Disability (r = 0.48) • Lack of High School Diploma (r = 0.45) • Lack of Health Insurance (r = 0.37)	• Household Income (r = -0.42) • Medical Professional Capacity (r = -0.39) (access to healthcare)

	Age 65 and Older	Lack of HS Diploma	Disability	Limited English Language Proficiency	Lack of Health Insurance	Lack of Vehicle	Unemployment Rate	Household Income	Income Inequality	Home Ownership	Single-Parent Household	Presence of Mobile Homes	Public School Capacity	Medical Professional Capacity	Hospital Capacity	Hotel/Motel Capacity	Rental Property Capacity	Affiliation with a Religion	Connection to Civic and Social Organizations	Population Change
Age 65 and Older	1.00	-0.12	0.41	-0.07	-0.15	-0.16	-0.11	-0.27	0.01*	-0.12	-0.31	0.13	0.23	-0.08	0.26	0.14	0.10	0.03*	0.21	-0.34
Lack of HS Diploma	-0.12	1.00	0.43	0.43	0.46	0.34	0.50	-0.59	0.37	-0.19	0.53	0.45	-0.12	-0.49	-0.01*	-0.11	-0.01*	0.02*	-0.15	-0.19
Disability	0.41	0.43	1.00	0.11	0.09	0.16	0.41	-0.66	0.24	-0.18	0.25	0.48	-0.03*	-0.34	0.04	-0.05	0.04*	-0.08	-0.02*	-0.39
Limited English Language Proficiency	-0.07	0.43	0.11	1.00	-0.04*	0.33	0.52	-0.31	0.28	-0.11	0.38	-0.20	-0.06	-0.14	-0.01*	-0.02*	0.02*	0.02*	-0.05	0.04*
Lack of Health Insurance	-0.15	0.46	0.09	-0.04*	1.00	0.11	0.16	-0.26	0.17	-0.29	0.28	0.37	0.09	-0.41	0.06	0.09	0.12	0.08	-0.08	0.07
Lack of Vehicle	-0.16	0.34	0.16	0.33	0.11	1.00	0.50	-0.30	0.39	-0.32	0.59	-0.05	-0.05	-0.12	-0.09	-0.06	-0.04*	-0.03*	-0.01*	-0.16
Unemployment Rate	-0.11	0.50	0.41	0.52	0.16	0.50	1.00	-0.50	0.41	-0.24	0.66	0.17	-0.16	-0.28	-0.13	-0.09	-0.01*	-0.12	-0.13	-0.13
Household Income	-0.27	-0.59	-0.66	-0.31	-0.26	-0.30	-0.50	1.00	-0.43	0.34	-0.48	-0.42	-0.05	0.42	-0.12	0.02*	-0.07	-0.04*	-0.01*	0.47
Income Inequality	0.01*	0.37	0.24	0.28	0.17	0.39	0.41	-0.43	1.00	-0.34	0.49	0.14	-0.12	-0.04*	-0.06	-0.06	0.04*	0.04*	-0.11	-0.08
Home Ownership	-0.12	-0.19	-0.18	-0.11	-0.29	-0.32	-0.24	0.34	-0.34	1.00	-0.28	-0.11	-0.20	0.30	-0.07	-0.30	-0.29	0.04*	-0.10	0.10
Single-Parent Household	-0.31	0.53	0.25	0.38	0.28	0.59	0.66	-0.48	0.49	-0.28	1.00	0.15	-0.25	-0.21	-0.19	-0.13	-0.05	-0.04*	-0.18	-0.14
Presence of Mobile Homes	0.13	0.45	0.48	-0.20	0.37	-0.05	0.17	-0.42	0.14	-0.11	0.15	1.00	0.01*	-0.39	0.02*	0.00*	0.04*	-0.12	-0.09	-0.17
Public School Capacity	0.23	-0.12	-0.03*	-0.06	0.09	-0.05	-0.16	-0.05	-0.12	-0.20	-0.25	0.01*	1.00	-0.18	0.38	0.33	0.12	0.22	0.27	-0.20
Medical Professional Capacity	-0.08	-0.49	-0.34	-0.14	-0.41	-0.12	-0.28	0.42	-0.04*	0.30	-0.21	-0.39	-0.18	1.00	-0.10	-0.09	-0.11	0.02*	-0.04*	0.19
Hospital Capacity	0.26	-0.01*	0.04*	-0.01*	0.06	-0.09	-0.13	-0.12	-0.06	-0.07	-0.19	0.02*	0.38	-0.10	1.00	0.21	0.08	0.26	0.29	-0.24
Hotel/Motel Capacity	0.14	-0.11	-0.05	-0.02*	0.09	-0.06	-0.09	0.0*	-0.06	-0.30	-0.13	0.00*	0.33	-0.09	0.21	1.00	0.25	0.05	0.24	-0.05
Rental Property Capacity	0.10	-0.01*	0.04*	0.02*	0.12	-0.04*	-0.01*	-0.07	0.04*	-0.29	-0.05	0.04*	0.12	-0.11	0.08	0.25	1.00	0.07	0.07	-0.03*
Affiliation with a Religion	0.03*	0.02*	-0.08	0.02*	0.08	-0.03*	-0.12	-0.04*	0.04*	0.04*	-0.04*	-0.12	0.22	0.02*	0.26	0.05	0.07	1.00	0.14	-0.15
Connection to Civic and Social Organizations	0.21	-0.15	-0.02*	-0.05	-0.08	-0.01*	-0.13	-0.01	-0.11	-0.10	-0.18	-0.09	0.27	-0.04*	0.29	0.24	0.07	0.14	1.00	-0.18
Population Change	-0.34	-0.19	-0.39	0.04*	0.07	-0.16	-0.13	0.47	-0.08	0.10	-0.14	-0.17	-0.20	0.19	-0.24	-0.05	-0.03*	-0.15	-0.18	1.00

**not statistically significant*

Positive relationships have green shading

Negative relationships have blue shading

Appendix F: National Average by Indicator

The following chart provides the national mean for each indicator.

Indicator	Measure (All Positive)	National Average
Population Indicators		
Educational Attainment	Percentage with a High School Diploma	87.7
Unemployment Rate	Percentage Employed	94.1
Disability	Percentage without a Disability	84.4
English Language Proficiency	Percentage Speaking Fluent English	96.6
Home Ownership	Percentage of Owner-Occupied Housing	36.2
Mobility	Percentage with Access to a Vehicle	91.3
Age	Percentage under 65	84.8
Household Income	Median Household Income	$60,273
Income Inequality	Gini Index	0.48
Health Insurance	Percentage with Health Insurance	90.6
Single-Parent Households	Percentage of Two-Parent Households (of all family households)	67.9
Community Indicators		
Connection to Civic and Social Organizations	Organizations per 10,000 People	.83
Hospital Capacity	Hospitals per 10,000 People	0.17
Medical Professional Capacity	Diagnostic Practitioners per 1,000 People	19
Affiliation with a Religion	Percentage of Religious Adherents	51.4
Presence of Mobile Homes	Percentage of Non-mobile Homes	93.8
Public School Capacity	Schools per 5,000 People	1.6
Population Change	Population Change	.72 standard deviation
Hotel/Motel Capacity	Hotels/Motels per 5,000 People	.83
Rental Property Capacity	Percentage of Vacant Rentals	6

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Appendix G: Aggregated Community Resilience Indicators — Counties in Lowest Two Bins

The counties in each list are ordered first alphabetically by state or the territory of Puerto Rico and then from lowest (more challenges to resilience) to highest (fewer challenges to resilience) scores.

Greene County, Alabama
Perry County, Alabama
Wilcox County, Alabama
Kusilvak Census Area, Alaska
Lee County, Arkansas
Clay County, Georgia
Quitman County, Georgia
Taliaferro County, Georgia
Wolfe County, Kentucky
Holmes County, Mississippi
Humphreys County, Mississippi
Bronx County, New York
Adjuntas Municipio, Puerto Rico
Aguadilla Municipio, Puerto Rico
Aguas Buenas Municipio, Puerto Rico
Arecibo Municipio, Puerto Rico
Cabo Rojo Municipio, Puerto Rico
Canovanas Municipio, Puerto Rico
Catano Municipio, Puerto Rico
Ciales Municipio, Puerto Rico
Cidra Municipio, Puerto Rico
Comerio Municipio, Puerto Rico
Corozal Municipio, Puerto Rico
Fajardo Municipio, Puerto Rico
Guanica Municipio, Puerto Rico
Guayama Municipio, Puerto Rico
Hormigueros Municipio, Puerto Rico
Isabela Municipio, Puerto Rico
Jayuya Municipio, Puerto Rico
Juncos Municipio, Puerto Rico
Lajas Municipio, Puerto Rico
Lares Municipio, Puerto Rico
Loiza Municipio, Puerto Rico
Luquillo Municipio, Puerto Rico
Maricao Municipio, Puerto Rico
Maunabo Municipio, Puerto Rico
Mayaguez Municipio, Puerto Rico
Moca Municipio, Puerto Rico
Naranjito Municipio, Puerto Rico
Orocovis Municipio, Puerto Rico
Patillas Municipio, Puerto Rico
Ponce Municipio, Puerto Rico
Rio Grande Municipio, Puerto Rico
Sabana Grande Municipio, Puerto Rico
San Juan Municipio, Puerto Rico
San Sebastiï¿½n Municipio, Puerto Rico
Utuado Municipio, Puerto Rico
Vega Alta Municipio, Puerto Rico
Vega Baja Municipio, Puerto Rico
Villalba Municipio, Puerto Rico
Yabucoa Municipio, Puerto Rico
Yauco Municipio, Puerto Rico
Allendale County, South Carolina
Buffalo County, South Dakota
Oglala Lakota County, South Dakota
Todd County, South Dakota
Hudspeth County, Texas
Kenedy County, Texas
Presidio County, Texas
Starr County, Texas
Zapata County, Texas

Barbour County, Alabama
Bullock County, Alabama
Choctaw County, Alabama
Clarke County, Alabama
Conecuh County, Alabama
Dallas County, Alabama
Hale County, Alabama
Lowndes County, Alabama
Macon County, Alabama
Marengo County, Alabama
Monroe County, Alabama
Sumter County, Alabama
Bethel Census Area, Alaska
Nome Census Area, Alaska
Northwest Arctic Borough, Alaska
Yukon-Koyukuk Census Area, Alaska
Apache County, Arizona
La Paz County, Arizona
Mohave County, Arizona
Navajo County, Arizona
Yuma County, Arizona
Chicot County, Arkansas
Dallas County, Arkansas
Desha County, Arkansas
Lafayette County, Arkansas
Monroe County, Arkansas
Phillips County, Arkansas
St. Francis County, Arkansas
Woodruff County, Arkansas
Imperial County, California
Merced County, California
Trinity County, California
Costilla County, Colorado
DeSoto County, Florida
Dixie County, Florida
Gadsden County, Florida
Glades County, Florida
Hamilton County, Florida
Hendry County, Florida
Highlands County, Florida
Holmes County, Florida
Lafayette County, Florida
Liberty County, Florida
Miami-Dade County, Florida
Okeechobee County, Florida
Putnam County, Florida
Suwannee County, Florida
Union County, Florida
Atkinson County, Georgia
Baker County, Georgia
Baldwin County, Georgia
Ben Hill County, Georgia
Berrien County, Georgia
Brantley County, Georgia
Brooks County, Georgia
Calhoun County, Georgia
Candler County, Georgia
Charlton County, Georgia
Clinch County, Georgia
Coffee County, Georgia
Colquitt County, Georgia
Crawford County, Georgia
Crisp County, Georgia
Decatur County, Georgia
Dooly County, Georgia
Dougherty County, Georgia
Echols County, Georgia
Elbert County, Georgia
Emanuel County, Georgia
Evans County, Georgia
Greene County, Georgia
Hancock County, Georgia
Irwin County, Georgia
Jefferson County, Georgia
Lincoln County, Georgia
Macon County, Georgia
Marion County, Georgia
Meriwether County, Georgia
Mitchell County, Georgia
Randolph County, Georgia
Seminole County, Georgia
Stewart County, Georgia
Sumter County, Georgia
Talbot County, Georgia
Taylor County, Georgia
Terrell County, Georgia
Treutlen County, Georgia
Twiggs County, Georgia
Warren County, Georgia
Wheeler County, Georgia
Wilkes County, Georgia
Clark County, Idaho
Alexander County, Illinois
Pope County, Illinois
Bell County, Kentucky
Breathitt County, Kentucky
Clay County, Kentucky
Elliott County, Kentucky
Estill County, Kentucky
Floyd County, Kentucky
Fulton County, Kentucky
Harlan County, Kentucky
Knott County, Kentucky
Lawrence County, Kentucky
Lee County, Kentucky
Leslie County, Kentucky
Letcher County, Kentucky
McCreary County, Kentucky
Magoffin County, Kentucky
Martin County, Kentucky
Owsley County, Kentucky
Perry County, Kentucky
Pike County, Kentucky
Claiborne Parish, Louisiana
Concordia Parish, Louisiana
East Carroll Parish, Louisiana
Jackson Parish, Louisiana
Madison Parish, Louisiana

Natchitoches Parish, Louisiana
Orleans Parish, Louisiana
Pointe Coupee Parish, Louisiana
Red River Parish, Louisiana
Sabine Parish, Louisiana
St. Helena Parish, Louisiana
Tensas Parish, Louisiana
Washington Parish, Louisiana
Baltimore city, Maryland
Lake County, Michigan
Oscoda County, Michigan
Adams County, Mississippi
Amite County, Mississippi
Attala County, Mississippi
Bolivar County, Mississippi
Claiborne County, Mississippi
Coahoma County, Mississippi
Issaquena County, Mississippi
Jefferson County, Mississippi
Jefferson Davis County, Mississippi
Kemper County, Mississippi
Leake County, Mississippi
Leflore County, Mississippi
Montgomery County, Mississippi
Noxubee County, Mississippi
Quitman County, Mississippi
Scott County, Mississippi
Sharkey County, Mississippi
Sunflower County, Mississippi
Tallahatchie County, Mississippi
Walthall County, Mississippi
Washington County, Mississippi
Wilkinson County, Mississippi
Yazoo County, Mississippi
Dunklin County, Missouri
Mississippi County, Missouri
Morgan County, Missouri
New Madrid County, Missouri
Pemiscot County, Missouri
Ripley County, Missouri
Shannon County, Missouri
Wayne County, Missouri
Nye County, Nevada
Essex County, New Jersey
Hudson County, New Jersey
Cibola County, New Mexico
Luna County, New Mexico
McKinley County, New Mexico
Mora County, New Mexico
San Miguel County, New Mexico
Sierra County, New Mexico
Socorro County, New Mexico
Union County, New Mexico
Kings County, New York
New York County, New York
Queens County, New York
Anson County, North Carolina
Bertie County, North Carolina
Bladen County, North Carolina
Columbus County, North Carolina
Duplin County, North Carolina
Edgecombe County, North Carolina
Greene County, North Carolina
Halifax County, North Carolina
Hertford County, North Carolina
Jones County, North Carolina
Lenoir County, North Carolina
Northampton County, North Carolina
Robeson County, North Carolina
Sampson County, North Carolina
Scotland County, North Carolina
Tyrrell County, North Carolina
Vance County, North Carolina
Warren County, North Carolina
Washington County, North Carolina
Sioux County, North Dakota
Adams County, Ohio
Delaware County, Oklahoma
McIntosh County, Oklahoma
Marshall County, Oklahoma
Philadelphia County, Pennsylvania
Aguada Municipio, Puerto Rico
Aibonito Municipio, Puerto Rico
Anasco Municipio, Puerto Rico
Arroyo Municipio, Puerto Rico
Barceloneta Municipio, Puerto Rico
Barranquitas Municipio, Puerto Rico
Bayamon Municipio, Puerto Rico
Caguas Municipio, Puerto Rico
Camuy Municipio, Puerto Rico
Carolina Municipio, Puerto Rico
Cayey Municipio, Puerto Rico
Ceiba Municipio, Puerto Rico
Coamo Municipio, Puerto Rico
Dorado Municipio, Puerto Rico
Florida Municipio, Puerto Rico
Guayanilla Municipio, Puerto Rico
Guaynabo Municipio, Puerto Rico
Gurabo Municipio, Puerto Rico
Hatillo Municipio, Puerto Rico
Humacao Municipio, Puerto Rico
Juana Diaz Municipio, Puerto Rico
Las Marias Municipio, Puerto Rico
Las Piedras Municipio, Puerto Rico
Manati Municipio, Puerto Rico
Morovis Municipio, Puerto Rico
Naguabo Municipio, Puerto Rico
Penuelas Municipio, Puerto Rico
Quebradillas Municipio, Puerto Rico
Rincon Municipio, Puerto Rico
Salinas Municipio, Puerto Rico
San German Municipio, Puerto Rico
San Lorenzo Municipio, Puerto Rico
Santa Isabel Municipio, Puerto Rico
Toa Baja Municipio, Puerto Rico
Trujillo Alto Municipio, Puerto Rico
Vieques Municipio, Puerto Rico
Abbeville County, South Carolina
Bamberg County, South Carolina
Barnwell County, South Carolina
Chesterfield County, South Carolina
Clarendon County, South Carolina
Darlington County, South Carolina
Dillon County, South Carolina
Fairfield County, South Carolina
Jasper County, South Carolina
Lee County, South Carolina
McCormick County, South Carolina
Marion County, South Carolina
Marlboro County, South Carolina
Orangeburg County, South Carolina
Williamsburg County, South Carolina

Corson County, South Dakota
Jackson County, South Dakota
Mellette County, South Dakota
Ziebach County, South Dakota
Benton County, Tennessee
Bledsoe County, Tennessee
Campbell County, Tennessee
Grundy County, Tennessee
Hancock County, Tennessee
Jackson County, Tennessee
Lake County, Tennessee
Lauderdale County, Tennessee
Brooks County, Texas
Cameron County, Texas
Dickens County, Texas
Dimmit County, Texas
Duval County, Texas
Falls County, Texas
Frio County, Texas
Hall County, Texas
Hidalgo County, Texas
Jim Hogg County, Texas
Kent County, Texas
Llano County, Texas
Loving County, Texas
Marion County, Texas
Maverick County, Texas
Menard County, Texas
Newton County, Texas
Polk County, Texas
Real County, Texas
Sabine County, Texas
San Augustine County, Texas
San Jacinto County, Texas
Shelby County, Texas
Trinity County, Texas
Webb County, Texas
Willacy County, Texas
Zavala County, Texas
Brunswick County, Virginia
Buchanan County, Virginia
Dickenson County, Virginia
Henry County, Virginia
Lee County, Virginia
Mecklenburg County, Virginia
Wise County, Virginia
Danville city, Virginia
Emporia city, Virginia
Franklin city, Virginia
Richmond city, Virginia
Boone County, West Virginia
Logan County, West Virginia
McDowell County, West Virginia
Mingo County, West Virginia
Roane County, West Virginia
Summers County, West Virginia
Webster County, West Virginia
Wyoming County, West Virginia
Menominee County, Wisconsin

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