Observational Verification of the Cumulative Resilience Screening Index (CRSI) Using Hurricanes, Inland Floods, and Wildfires From 2016 to 2019

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Abstract Users can apply three processes to develop confidence in decision-making tools like models and indices—validation, verification, and observation. The utility of the Cumulative Resilience Screening Index (CRSI) was demonstrated by combining the processes of verification and observation using real-world natural hazard events (i.e., hurricanes, inland flooding, and wildfires). The ability of CRSI to determine the counties most vulnerable to hazards and least likely to recover quickly from natural hazards is demonstrated using these natural hazard events from outside the original index construction data set. Using Hurricane Harvey and Hurricane Michael, the counties in Texas and Florida/Georgia, respectively, experiencing the most damage and the most extended recovery intervals were determined accurately. Similarly, the most vulnerable and least recoverable counties were correctly identified as those associated with the Great Louisiana Flood of 2016. Finally, three different types of wildfires in California were examined to determine the likelihood of recovery and the strength of pre-event planning. All models and indices developed for use by decision-makers should consider undertaking this verification or a similar validation operation to enhance user confidence.

Plain Language Summary The manuscript provides a set of observational verifications of the Cumulative Resilience Screening Index that uses hurricanes, floods, and wildfires in the period of 2016–2019. These verifications will provide users with additional confidence in the results of the index.

1. Introduction

Verification, validation, and observations are approaches for testing models and indices to assess the confidence (both qualitatively and quantitatively) users can have in the proposed model or index. These procedures can reduce the risk of using the "mathematical tools" and enhance the users' confidence in the results. Verification is one of the primary processes for building credibility in statistical indices (Thacker et al., 2004). Detailed indices are easily tested for structural and results-oriented correctness by collecting data outside those utilized for the model construction and completing a validation test comparing the model "predictions" with the observed data. Verification is primarily an assessment that the processes providing a model or index result are performing accurately and the results correctly provide an assessment of some event outside the index's or model's construction data set.

Validation is a process that examines whether a model is an accurate representation of the natural world and provides accurate results (AIAA, 1998). Validation tends to be a rigid mathematical process comparing the predicted result and the observed result, whereas verification can be a mathematical process as well but usually is not. It can be simply a narrative evaluation of the model or index processes. If these processes are appropriate, the index can foretell the result of an activity or event outside the construction data set (AIAA, 1998).

Similar to the informal approach of verification, observation is simply a process whereby users examine the results of a model or index "prediction" of some future event and assesses whether they "believe" the result. This belief is usually that the model or index result correctly indicates the outcome of some activity or event outside the data used to construct the model or index. This comparison of model/index results to future results tends to instill confidence in the users' application of the model or index.

Unfortunately, some indices are not straightforward producing results that can be easily validated. These tools or indices indicate a process result rather than a specific number that can be compared to future measured data. The Cumulative Resilience Screening Index (CRSI; Summers et al., 2020) is this type of tool. The index assesses a score representing a county's potential resilience to natural hazards based on past events. However, using the

combination of observation and verification (or observational verification), the CRSI score can be utilized to determine a county's likely resilience to upcoming natural hazards and determine which counties have poorer resilience to such risks. The concept of resilience is assessed by comparing scores for counties that have experienced a natural hazard and determining if CRSI accurately selected the counties most vulnerable to an event and most unlikely to be resilient in their recovery from an event. However, it may take years, or even decades, for counties to provide the information necessary for a quantitative test of which counties are the least resilient, in the long term, to any specific natural hazard. Even after that period of time, the resulting data set may be inadequate to characterize community-level resilience.

The conceptual construction and results of CRSI are entirely described in Summers et al. (2017, 2018) and there is no need for further discussion of the construction of these attributes beyond a simple summary (provided in Methods section). There are many potential users for CRSI, including, EPA Program Office and Regional users, State government users, County/Parish-level emergency and planning personnel, and individual community planners. EPA and state personnel could use CRSI to understand the areas of the county that may need greater recovery support or regional personnel to support pre-positioning needs for natural hazards. Most natural hazard planning is conducted at the county level or in individual metropolis areas. These users, as well as specific community users, can employ CRSI to assess local needs and help determine resilience capacity-building strategies. All of these users are projected as potential end-users of CRSI and its verification. Further development of users' confidence in the CRSI results is described here using natural hazard events outside the period used to construct the index. Using natural hazards like hurricanes, floods, and wildfires that occurred after the 2000–2015 period of natural hazards used to create CRSI and correctly assessing the counties most vulnerable or least recoverable from these events provides the users of CRSI with a verification of the index results and should instill confidence in its use.

2. Methods

The final conceptualization of the CRSI is discussed in Summers et al. (2020) and includes five domains comprised of 20 indicators (Figure 1). In the development of the CRSI index, the history of acute meteorological events were assessed throughout the United States as well as the governance, environmental, economic and social challenges these events created. Twelve acute meteorological event and natural hazard types were determined from a review of the National Climate Assessment (Melillo et al., 2014) and the 100 Resilient Cities report (ARUP, 2014) and are included in CRSI: drought, high winds, coastal flooding, inland flooding, wildfires, earthquakes, hurricanes, tornadoes, landslides, hail, extreme low temperatures, and extreme high temperatures. The final conceptual model of CRSI includes five domains which are comprised of 20 indicators that are derived from 117 unique metrics (Figure 1). A summary and discussion of the domains, indicators and types of metrics used in CRSI can be found in Summers et al. (2017, 2018, 2020) and are documented and summarized here in Table 1.

As an example, the risk domain is comprised of two indicators (i.e., exposure and loss) which are, in turn, comprised of 17 and 3 metrics, respectively (see Table 1). Each metric is determined from existing data from readily available sources (see Appendix A in Summers et al., 2020) and is represented as a value, usually a probability of occurrence, for each county. These individual metric values are normalized on a scale of 0–100 based on their national distribution to make them unitless so they can be combined for a county to create an indicator score—in this case for exposure and loss. Then, the resultant indicator scores are again normalized based on national distribution to create values between 0 and 100 for the indicators of exposure and loss for each county. These two indicator scores are combined for each county to create the Risk Domain Score.

All domains for each county, parish and borough (all referred to as county below) in the United States were min-max standardized on a scale from 0.01 to 0.99. The final CRSI calculation begins as a scaled value for recoverability/vulnerability derived from Governance and Risk (basic CRSI) with the Governance value being adjusted by the remaining domain scores for Social, Built Environment and Natural Environment to complete the calculation of CRSI as shown below:

$$\text{CRSI(B)}i = R_i/V_i$$

where CRSI(B)i = value of basic resilience (recovery/vulnerability or R_i/V_i) and R_i/V_i = Governance in county i/risk in county i.
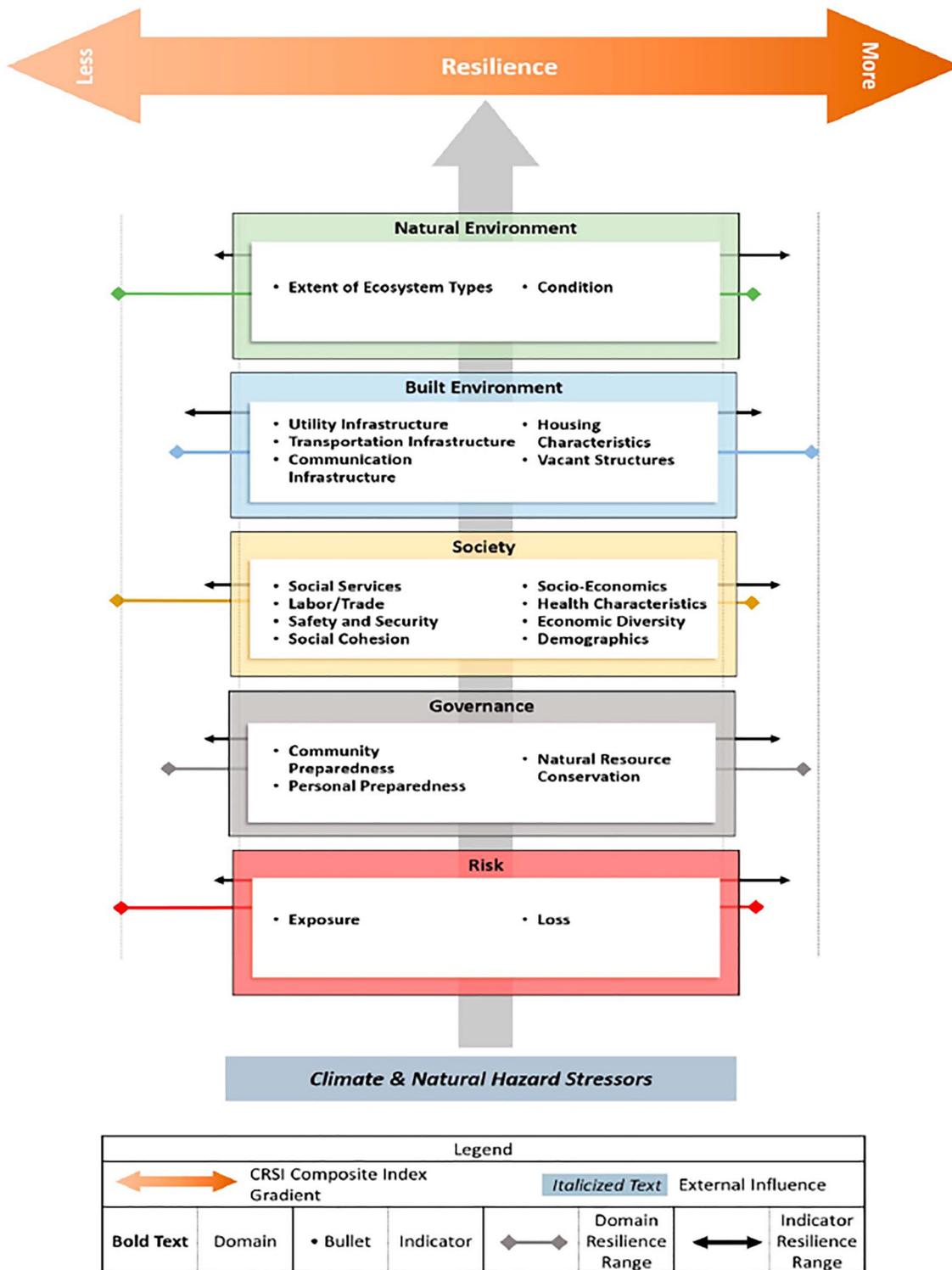
Figure 1. Cumulative Resilience Screening Index (CRSI) conceptual framework. Arrows projected from boxes to the left and right represent hypothetical increases and decreases in ranges for indicators (black arrows) and domains (colored arrows).

Table 1
List of Cumulative Resilience Screening Index (CRSI) Domains, Indicators, Scope, and Number of Metrics

Domain	Indicators(s)	Metric category (number of specific metrics)
Risk (2/20)	Exposure	Earthquake probability (1)
		Extreme High Temperature Incidents (1)
		Extreme Low Temperature Incidents (1)
		Flood Probability (2)
		Hailstorm Probability (1)
		Tornado Probability (2)
		Hurricane Probability (2)
		Landslide Probability (1)
		Major Toxics Presence (1)
		Non-Storm Damaging Wind Incidents (1)
		Location of Nuclear Facilities (1)
		Location of RCRA sites (1)[a]
		Location of Superfund Sites (1)[b]
		Toxic Release Presence (1)
		Wildfire Probability (1)
	Loss	Developed Area Loss (includes human and property measures) (1)
		Natural Area Loss (1)
		Dual-Benefit Area Loss (includes cropland and managed area measures) (1)
Governance (3/5)	Community	
	Preparedness	Community resilience strengthening (2)
	Natural Resource Conservation	Natural Resource Recovery (1)
	Personal Preparedness	Personal Property Hazard Protection (2)
Built Environment (5/24)	Communications	
	Infrastructure	Communications Continuity (7)
	Housing	
	Characteristics	Structure vulnerability (5)
	Transportation	
	Infrastructure	Transportation Flow Continuity (6)
	Utility Infrastructure	Utility Continuity (3)
	Vacant Structures	Structure Vulnerability (3)
Natural Environment (2/18)	Extent of Ecosystem Types	Marine/Estuarine Area (1)
		Agriculture Area (1)
		Forested Area (1)
		Grassland Area (1)
		Inland Surface Water Area (1)
		Perennial Ice/Snow Area (1)
		Protected Areas (1)
		Tundra Area (1)
		Wetland Area (1)

Table 1
Continued

Domain	Indicators(s)	Metric category (number of specific metrics)
	Condition	Biodiversity, using Birds as Proxy (1)
		Coastal Condition (1)
		Forest Condition (1)
		Inland Lake Condition (1)
		Percentage of Clean Air Days (1)
		Rivers and Streams Condition (1)
		Soil Growth Suitability (1)
		Soil Productivity (1)
		Wetlands Condition (1)
Society (8/50)	Demographics	Vulnerable Population (5)
	Economic Diversity	Economic Stability/Recovery (2)
	Health Characteristics	Health Problems That May Impact Personal Resilience (9)
	Labor and Trade Services	Construction Recovery (8)
	Safety and Security	Provisioning of Emergency and Civil Services (4)
	Social Cohesion	Access to Social Support (4)
	Social Services	Access Provisioning to Critical Services (15)
	Socio-Economics	Employment Opportunity (1)
		Personal Economics (2)

Note. Numbers in parentheses for domains show the total.
[a]RCRA (Resource Conservation and Recovery Act). [b]Superfund EPA's Superfund Program is responsible for cleaning up severely contaminated sites.

The overall CRSI score is calculated as:

$$\text{CRSI}i = (\text{Gov}i + \text{Soc(a)}i\text{Gov}i + \text{NE(a)}i\text{Gov}i + \text{BE(a)}i\text{Gov}i)/\text{Risk}i$$

where $\text{CRSI}i$ = the value of CRSI or adjusted resilience for county i, and $\text{Soc(a)}i$, $\text{BE(a)}i$, and $\text{NE(a)}i$ are the adjustment multipliers for Society, Built Environment, and Natural Environment in each county i, and $\text{Risk}i$ is the Risk score for county i.

These indicators were derived from 117 unique metrics (Table 1). The strategy used to select the domains, indicators, and metrics, as well as their values is entirely described in Summers et al. (2020) and are summarized here for completeness. The domains included in CRSI include risk, governance, society, built environment, and natural environment. The concept of basic community resilience to natural hazards is being driven in CRSI by the likelihood of an natural hazard event occurring (risk) and the community's preparation for such an event (governance); therefore, the domains of risk and governance are included at the base of the conceptual model (Figure 1) to denote basic resilience as some relationship between risk and preparedness for that risk (governance). The remaining domains include elements that could exacerbate (increase) or diminish (decrease) the vulnerability to an event or the potential for recovery after the event. These domains include society, built environment, and natural environment. Societal indicators that can modify vulnerability to an event or recovery from the event include the availability of social services, the type of available labor or trades within the community, safety and security requirements, the socioeconomics and economic diversity of the community, the health characteristics and availability of health care access in the community, basic demographic information concerning the community, and the cohesiveness of the community. Built environment indicators that can modify vulnerability or recovery include multiple infrastructure elements—communications, utilities, and transportation—and housing characteristics. Twenty-four metrics are compiled to represent the built environment. The natural environment domain describes the resilience of natural and managed ecosystems through ecosystem extent and condition measures. Eighteen metrics are combined to define the indicators within the natural environment domain. Given that this exercise is

Table 2
National Averages for Cumulative Resilience Screening Index (CRSI), CRSI Domains, and Basic Resilience (Governance/Risk)

Risk	Governance	Basic resilience	Built environment	Natural environment	Society	CRSI
0.229	0.597	2.607	0.393	0.413	0.516	4.321

to verify CRSI against natural hazard events post-2015, the specifics pertaining to the index construction, equations and lists of indicators and metrics are provided, in detail, elsewhere (Summers et al., 2017, 2018, 2020).

Secondary data from established, publicly accessible sources served as the foundation for developing CRSI (Summers et al., 2020). Nationally consistent, county-level or equivalent-scale data available within the 2000–2015 time frame were targeted for inclusion in the index. Metadata were reviewed to ascertain appropriateness for use in CRSI. Collected data were age, population, or land area-weighted, as appropriate. All standardized values were geolocated to the county. Because contributed data were not annually consistent, standardized values were averaged across years within each county or county-equivalent unit. Mean data were normalized on a 0 to 1.0 scale to form the metric basis for CRSI. The complement of data represents 3,135 of 3,143 counties and county-equivalents (e.g., parishes and boroughs), excluding eight boroughs from Alaska that were not included due to lack of information.

All domains for each county, parish, and borough (all referred to as county below) were min-max standardized on a scale from 0.01 to 0.99. The final CRSI calculation begins as a scaled value for recoverability/vulnerability derived from governance and risk (basic resilience). Then, the basic resilience value is adjusted by the remaining domain scores for the social, built environment, and natural environment to represent an enhancement of or diminution of basic resilience to complete the calculation of CRSI. All CRSI results were determined from the original 2000–2015 data set (Summers et al., 2020) and used to compare to events occurring during 2016–2019. The CRSI results are those reported in Summers et al. (2017, 2020). In each verification case, the CRSI results from 2000 to 2015 are compared to the year of a natural hazard occurring after 2015 (e.g., Hurricane Harvey in 2016, Hurricane Michael in 2018, or the Great Inland Louisiana Flood in 2016). The 2000–2015 CRSI results compare the resilience attributes of all the counties encountering the new event and "projects" which counties/parishes would be among the least resilient.

Natural hazards events during the period 2016–2019 were determined from similar public data sources (Summers et al., 2022). The risk data set was expanded to contain yearly natural hazard exposure estimates at the county-level for all 50 United States (US) and Puerto Rico (PR) across a 20-year timespan (2000–2019). This permits the identification of natural hazards during the 2016–2019 time frame that were not part of the original CRSI data. Secondary data sources were used to collect tabular and spatial hazard exposure information for the nine natural hazards (e.g., hurricanes, tropical storms, tornadoes, landslides, wildfires, drought, coastal and inland flooding, and earthquakes) (Summers et al., 2022). Candidate secondary data were reviewed for accessibility, temporal and spatial scale, and data formatting. Data acceptance criteria were open access, per year basis, and vector or raster data format. When multiple data sources were available for the same natural hazard, data sets were compared, and the source most likely to continue publishing data was selected. In cases where data did not fully meet acceptance criteria, the best available data were used for further analysis. Hurricane, inland flood, and wildfire natural hazard events from the 2016–2019 period were selected and used for the CRSI observational verification process.

3. Results and Discussion

Two hurricane events, one significant flooding event, and three wildfires occurring in the 2016–2019 time frame are used to verify the results of the CRSI index developed from natural hazards information and county information from 2000 to 2015. The national results from CRSI are shown in Table 2. The verifications using Hurricane Harvey from 2017, Hurricane Michael from 2018, the great Louisiana Inland Flood in 2016, and the Thomas, Clayton, and Camp Fires (2016–2018) are described below and show the general accuracy of the "prediction" results of the CRSI index.

Table 3
Cumulative Resilience Screening Index (CRSI) and Domain Scores for Select Counties Along the Texas Gulf Coast Associated With the Path of Hurricane Harvey

County	Risk	Governance	Basic resilience	Built environment	Natural environment	Society	CRSI
Aransas	0.180	**0.573**	3.183	**0.334**	0.522	**0.404**	**3.070**
Brazoria	**0.602**	0.662	**1.099**	0.776	0.549	0.524	**2.694**
Calhoun	0.217	**0.505**	**2.327**	0.435	0.490	**0.429**	**2.808**
Chambers	**0.571**	0.615	**1.077**	0.511	0.500	**0.440**	**1.567**
Fort Bend	**0.411**	0.644	**1.567**	0.785	0.420	0.580	**3.545**
Galveston	**0.610**	0.753	**1.234**	0.608	0.472	**0.408**	**1.257**
Harris	**0.758**	0.611	**0.806**	0.837	**0.192**	0.491	**1.345**
Jackson	0.121	**0.586**	4.843	**0.337**	0.481	0.538	5.510
Jefferson	**0.530**	**0.534**	**1.008**	0.698	0.449	0.521	**2.005**
Matagorda	**0.256**	**0.545**	**2.129**	0.440	0.503	**0.431**	**2.677**
Nueces	**0.465**	0.639	**1.374**	0.669	0.419	**0.477**	**2.518**
Refugio	0.116	0.631	5.440	**0.266**	0.468	**0.443**	**3.961**
San Patricio	0.189	0.615	3.254	0.489	0.444	**0.402**	**3.860**
Victoria	0.141	**0.533**	3.780	0.512	0.510	0.541	6.348

Note. Bold denotes significantly below the national average for CRSI, below the national averages for all domains except risk which denotes above the national average, and below the national average for basic resilience.

3.1. Hurricane Harvey

Hurricane Harvey had two landfalls in Texas in August 2017—Port Aransas, TX in Nueces County and Rockport, TX in Aransas County. Also, heavy precipitation from Hurricane Harvey caused massive flooding in Brazoria and Harris Counties, TX, and areas around Houston and surrounding areas (e.g., Jefferson and Chambers Counties and Beaumont). Some of the worst wind damage occurred in the coastal city of Rockport, which lay directly in the storm's path. In Rockport and surrounding areas, the storm toppled power poles and destroyed many structures as a result of wind and storm surge. Similarly, Port Aransas, TX, received extensive damage. It was estimated that it would take a long time before the storm's catastrophic damage was repaired. Some areas are still recovering. Flooding in the Houston and Beaumont areas was the worst in history and displaced millions of people. CRSI results were examined to determine likely locations of observed low resilience and extensive damage along the Texas Gulf Coast (Table 3). Of these counties, CRSI scores for Jefferson, Chambers, and Harris Counties were significantly below the national average suggesting lower resilience to natural hazard events.

Similarly, Aransas and Refugio Counties (first Texas landfall) display low-risk domain scores suggesting a minimal recent history of significant natural hazards events (until Hurricane Harvey). However, both counties have significantly reduced built environment domain scores, implying that if a hurricane were to strike these counties, both could suffer significant structural damage due to reduced public infrastructure and increased proportions of vacant buildings. In addition, both counties displayed lower than national average society domain scores. These lower scores suggest that neither county has the diversity of skills needed to rebuild quickly nor do they have robust security and security infrastructures. While CRSI suggests this from the 2000–2015 data, other factors can certainly alter this interpretation. Before post-hazard approaches are completely evaluated, the users should consult local experts and examine specific issues. For example, post-Harvey, many influential homeowners and county leaders mobilized efforts to secure millions in recovery resources and put Aransas County at the forefront of regional recovery. Refugio County, conversely, has struggled to make progress. Hence, the CRSI results and this verification demonstrate that while both counties had seemingly similar issues prior to the hurricane, there were important differences at the local level. These differences can matter both in the strategic approaches taken post-recovery and in influencing future resilience.

Hurricane Harvey significantly impacted Port Aransas, TX, in Nueces County. CRSI scores for Nueces County show a substantially higher risk domain score than the national average, likely the result of historical hurricane paths. The largest metropolitan area in Nueces County is Corpus Christi, TX. This city avoided the devastation associated with this hurricane; however, Port Aransas, suffered extensive structural damage. Port Aransas is similar to Rockport, TX, in Aransas County with a significantly lower than average CRSI score.

Other coastal Texas counties with lower CRSI scores—Chambers (1.57), Harris (1.35), and Jefferson (2.01)—all have high risk-domain scores, significantly above the national average. Brazoria County, located southwest of Harris County, has an average CRSI score but a substantially higher than average risk-domain score. All four counties were significantly flooded due to the intense rainfall associated with Hurricane Harvey. Houston (in Harris County) had historic flooding that did not diminish for months following the storm. County-wide significant technological risks increase Harris County's risk score (e.g., chemical and oil refinery facilities, Superfund sites).

The resilience to flooding in these counties varies based on differing factors associated with the CRSI and domain scores. Harris County has one of Texas's highest risk-domain scores (0.758), generally associated with flooding and several exacerbating factors. The CRSI score for Harris County (1.35) is significantly below the national average, suggesting recovery from a significant natural hazard could be a very long process. This lowered resilience seems to be driven by a low natural environment score (0.192), which appears to result from increased development in the last decade and the significant loss of natural lands (particularly to the north and west of Houston). Wetlands and natural, open lands often significantly ameliorate acute natural hazard events (Alongi, 2008; Cai et al., 2011; Kuenzer & Renaud, 2012). These ecosystems are usually damaged by natural hazards (or anthropogenic threats) but tend to recover quickly while reducing the event's impact on surrounding populated areas. The low natural environment-domain score for the Houston area (often replaced by impervious surfaces) enhances the likelihood of significant flooding damage.

Brazoria County has an average resilience score that appears to be driven by high risk. The higher-level remaining factors reduce the risk and increase the overall resilience score to 2.70 (about the national average). Jefferson and Chambers Counties also have high risk-domain scores generally associated with flooding, and both counties display significantly lower than average resilience scores. However, the remaining domain scores in both counties suggest a more rapid recovery than Harris County would be expected for Chambers County but at a slower rate than Jefferson County.

3.2. Hurricane Michael

In October 2018, Hurricane Michael was a mighty and destructive Category 5 hurricane making landfall along the northeastern coastal region of the Gulf of Mexico and proceeding northward through the Florida panhandle and into southwestern Georgia. The low-pressure area originated in the Caribbean Sea on October 1, slowly developed into a hurricane off Cuba on October 8, and approached the Florida Panhandle as a Category 5 storm with peak winds of 160 mph, reaching landfall near Mexico Beach, FL (Bay County) on October 10. The hurricane moved inland, downgraded to a tropical storm over Georgia, and dissipated by October 16. At least 74 deaths and over $25 B in damages were attributed to the hurricane.

Catastrophic and widespread damage occurred in Bay County, FL, where Hurricane Michael made landfall. Over 45,000 structures were damaged, and about 1,500 of these were destroyed (Beven et al., 2019). High watermarks, determined by the U.S. Geological Survey, reached about 14 feet above ground level (Beven et al., 2019). Significant structural damage occurred at Tyndall Air Force Base (Bay County), with every building being damaged, and at least 20,000 people were displaced in Panama City, FL (Bay County) (Thrush, 2018). While the western edge of the storm affected all Florida counties westward in the Panhandle, the hurricane progressed northward through Jackson County as a Category 3 storm, significantly damaging the forested area between Panama City and Marianna, FL (Jackson County), resulting in heavy structural damage. Hurricane Michael progressed into southwestern Georgia as a Category 2 storm causing structural and tree damage and significant agricultural losses (~$2.5 B). These agricultural losses included a generational level loss to pecan farms. Agricultural losses were to the entire crop in Seminole County, GA, and 85% of Decatur County, GA. Additionally, cotton and vegetable crops were largely wiped out, and significant losses occurred to poultry farms (Fabian, 2018).

Table 4
Cumulative Resilience Screening Index (CRSI) and Domain Scores for Select Counties Along the Texas Gulf Coast Associated With the Path of Hurricane Michael

County	Risk	Governance	Basic resilience	Built environment	Natural environment	Society	CRSI
Florida							
Bay	**0.266**	**0.464**	**1.744**	0.588	0.520	**0.406**	**2.768**
Calhoun	0.111	**0.205**	**1.847**	**0.243**	**0.396**	**0.458**	**1.014**
Franklin	0.163	**0.435**	2.669	**0.287**	0.608	0.667	**4.195**
Gadsden	0.133	**0.202**	**1.519**	**0.307**	0.535	**0.461**	**1.575**
Gulf	0.160	**0.173**	**1.081**	0.375	0.453	**0.442**	**1.063**
Holmes	0.104	**0.317**	3.048	**0.284**	0.434	**0.455**	**2.212**
Jackson	0.143	**0.259**	**1.811**	0.433	0.469	**0.430**	**2.058**
Liberty	0.193	**0.227**	**1.176**	**0.195**	**0.265**	0.713	**0.935**
Taylor	0.115	0.617	5.365	**0.326**	**0.398**	**0.444**	**3.961**
Wakulla	0.216	**0.335**	**1.551**	0.353	0.483	0.640	**2.270**
Washington	0.147	**0.301**	**2.048**	0.341	0.431	**0.485**	**1.939**
Georgia							
Decatur	0.120	**0.081**	**0.675**	0.357	0.482	**0.453**	**0.681**
Seminole	0.159	**0.201**	**1.264**	0.223	0.428	**0.461**	**0.717**

Note. Bold denotes significantly below the national average for CRSI, below the national averages for all domains except risk which denotes above the national average, and below the national average for basic resilience.

CRSI results were examined (after the fact) to determine the magnitude and likely locations of extensive damage and low resilience along the Florida Panhandle and southwestern Georgia (Table 4). Hurricane Michael significantly impacted 11 counties in Florida (Governor's Executive Disaster Order included 35 Florida counties) and two counties in Georgia. Of these counties, CRSI scores for all Florida and Georgia impacted counties are below the national average, with all except Franklin and Taylor Counties (FL) being less than half the national average. In short, nearly all the counties were very vulnerable to a major hurricane.

Bay County suffered the most deaths and the most significant property damage. This county has a CRSI score about 36% below the national average and a basic resilience score about 33% below the national average. Bay County also has the highest built environment-domain score (0.588) of the counties impacted (well above the national average), suggesting attempts to prepare itself for natural hazards. However, the county's high number of vacant structures provides a basis for structural damage (Figure 2). While Bay County has the highest risk-domain score, the second-highest governance domain score, and the seventh basic resilience score, these domain scores reflect the likely impact of an average storm and not a century storm like the Category 5 Hurricane Michael. Probably, no amount of built environment code structure, enforcement, or infrastructure could have lessened the damage resulting from such a storm. However, the risk and governance domain scores suggest that significant damage would have occurred even if Hurricane Michael had been a lesser storm, though Bay County's built environment and social domain scores would have enhanced the county's recovery rates (the county is still recovering over 4 years later). Lower labor-trade services and social cohesion in Bay County suggest that recovery times would be lengthy (Figure 2). The index suggests that the highest proportional losses would occur in southwestern Georgia, where risk scores are low and governance scores are deficient (more than 86% and 66% below the national average for Decatur and Seminole Counties, GA, respectively) (Table 4). These are the counties where generational-level agricultural losses were observed. Low historical levels of failure coupled with deficient levels of community preparedness and high levels of vacant structures made Decatur County highly vulnerable to a natural hazard (Figure 3). Lower scores for governance in Calhoun, Gulf, Jackson, and Liberty Counties (FL) coupled with lower risk scores indicate that these counties were not as prepared as coastal counties like Bay, Franklin, and Wakulla Counties for a major hurricane. For example, relatively high levels of vacant structures, minimal natural resource conservation, lower levels of personal preparedness, communication and utility infrastructure made Jackson County
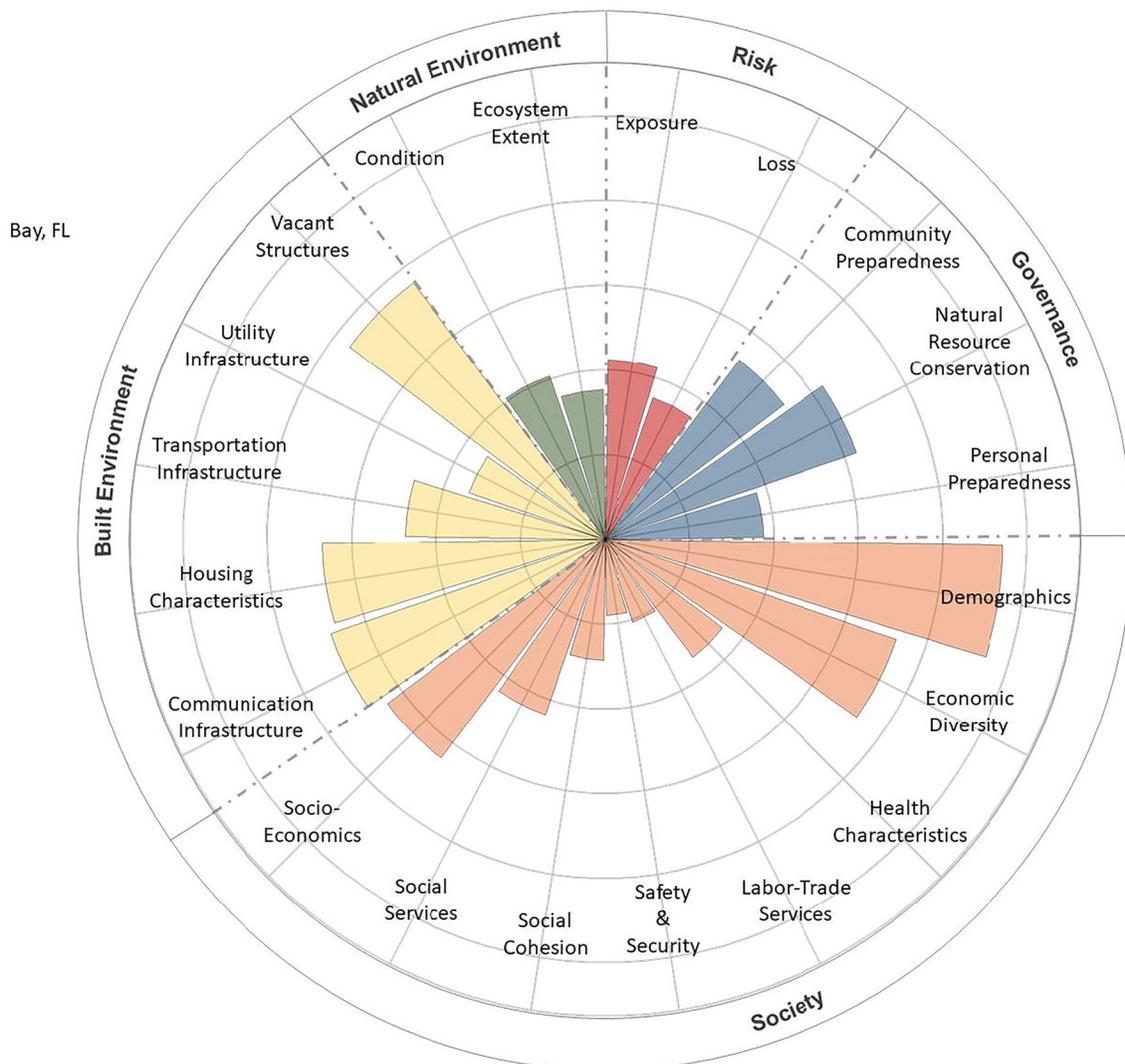
Figure 2. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to Bay County, Florida domain scores.

particularly vulnerable (Figure 4). These inland counties and the further inland Georgia counties may represent future resilience needs for non-coastal counties where more intense and longer-lasting storms may be prevalent (Summers et al., 2022).

3.3. Louisiana Flood (2016)

In August 2016, an unpredictable storm with prolonged rainfall (11–14 August 2016) resulted in massive flooding in lower Louisiana. The flood impacted 21 parishes in lower Louisiana (Table 5), submerging thousands of homes. Many rivers in the area reached record levels (e.g., Amite and Comite Rivers), and rainfall exceeded 20 inches in many parishes. Because many of the homeowners in these parishes were without flood insurance, this flood is considered one of the worst natural disasters in this area (Yan & Flores, 2016). Full flooding began on August 12, and by August 15, more than 10 rivers in the region had reached a moderate to record flood stage. As many as eight rivers reached record flood levels, including the Amite River and the Comite River, which crested at about 6.5 feet above the 65-year historical record of 51.91 feet (set in 1977) and about 4 feet above the 70-year historical record of 30.99 feet (established in 2001), respectively (AIR Worldwide, 2016). Approximately 200 roadways (including Interstates 10 and 12) became impassable due to flooding and there was potential damage
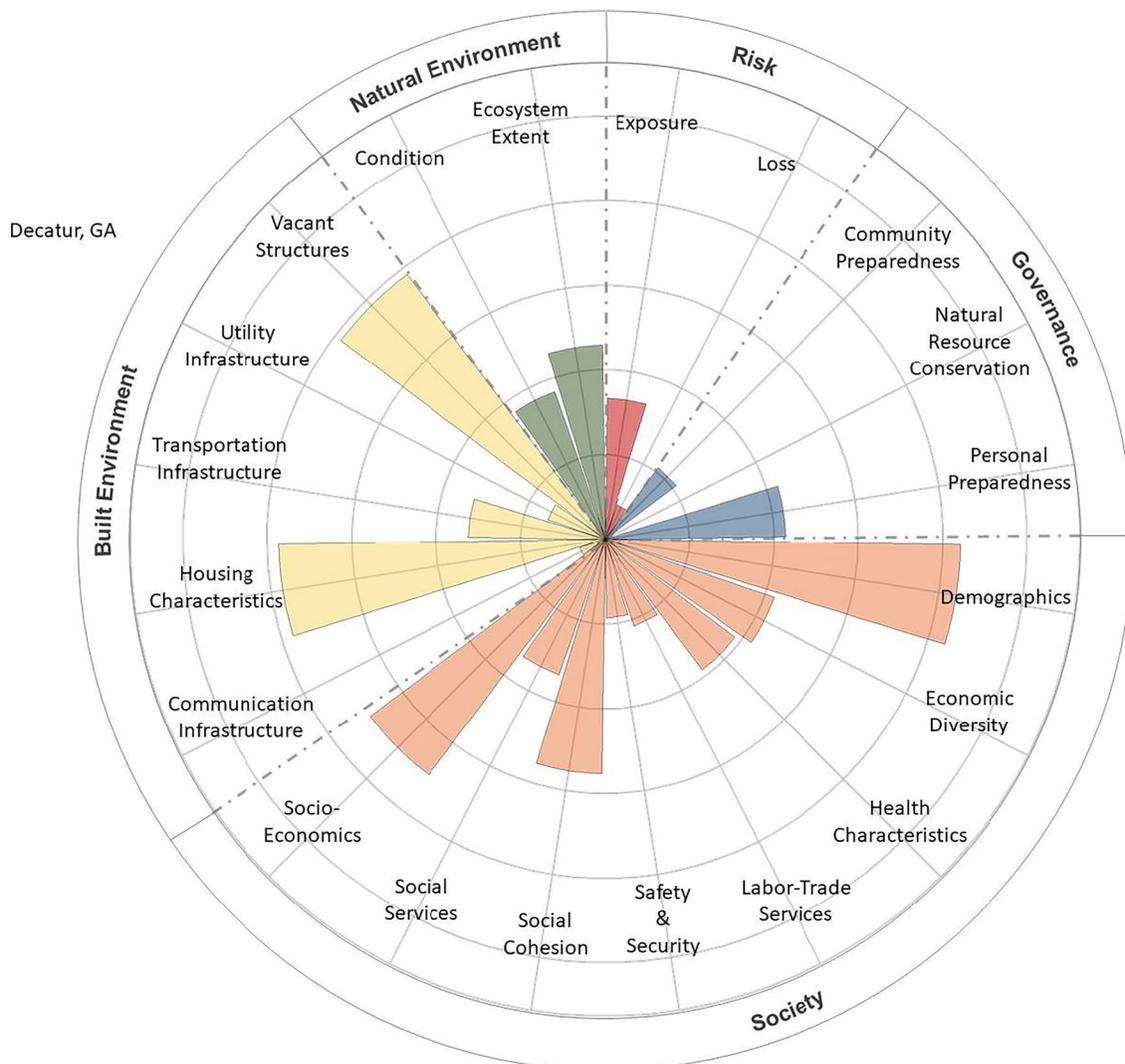
Figure 3. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to domain scores for Decatur County, Georgia.

to about 1,400 bridges that needed to be inspected before reopening. Stranded cars remained on highways (AIR Worldwide, 2016).

Examination of the CRSI scores and the basic resilience scores of the parishes impacted by the 2016 Louisiana flood show that all 21 parishes have scores below the national average; a significant number of them have scored substantially below the national average (Table 5). Therefore, the assessment becomes which of the highly vulnerable parishes were the most susceptible to flood exposure, potentially least prepared and, most likely to experience poor recovery rates. All parishes have a higher risk or exposure likelihood than the nation (except St. Helena Parish, which is about 10% lower than the national average), and all but five parishes (Avoyelles, Iberville, Pointe Coupee, Vermilion, and West Feliciana) have governance scores below the national average. Two of the lower-scoring parishes (St. Tammany and Washington; 0.41 and 0.30, respectively) are roughly 30% and 50% below the national scores for governance. As a result, all 21 parishes have below-average basic resilience scores, with eight parishes being less than 50% of the national average (Table 5). The combination of high risk and low governance makes these parishes highly vulnerable to a natural hazard (e.g., flooding), less likely to be prepared for such an event, and more likely to experience difficulties recovering from the event. Parishes like Ascension, St. Tammany, and Washington with CRSI scores of <1.0 are very vulnerable and not very resilient. Parishes like East Baton Rouge, East Feliciana, Iberia, Iberville, Jefferson Davis, Lafayette, Livingstone, St. Helena, St. Martin, and West Baton Rouge are also highly vulnerable with slow recovery rates and CRSI scores between 1.0
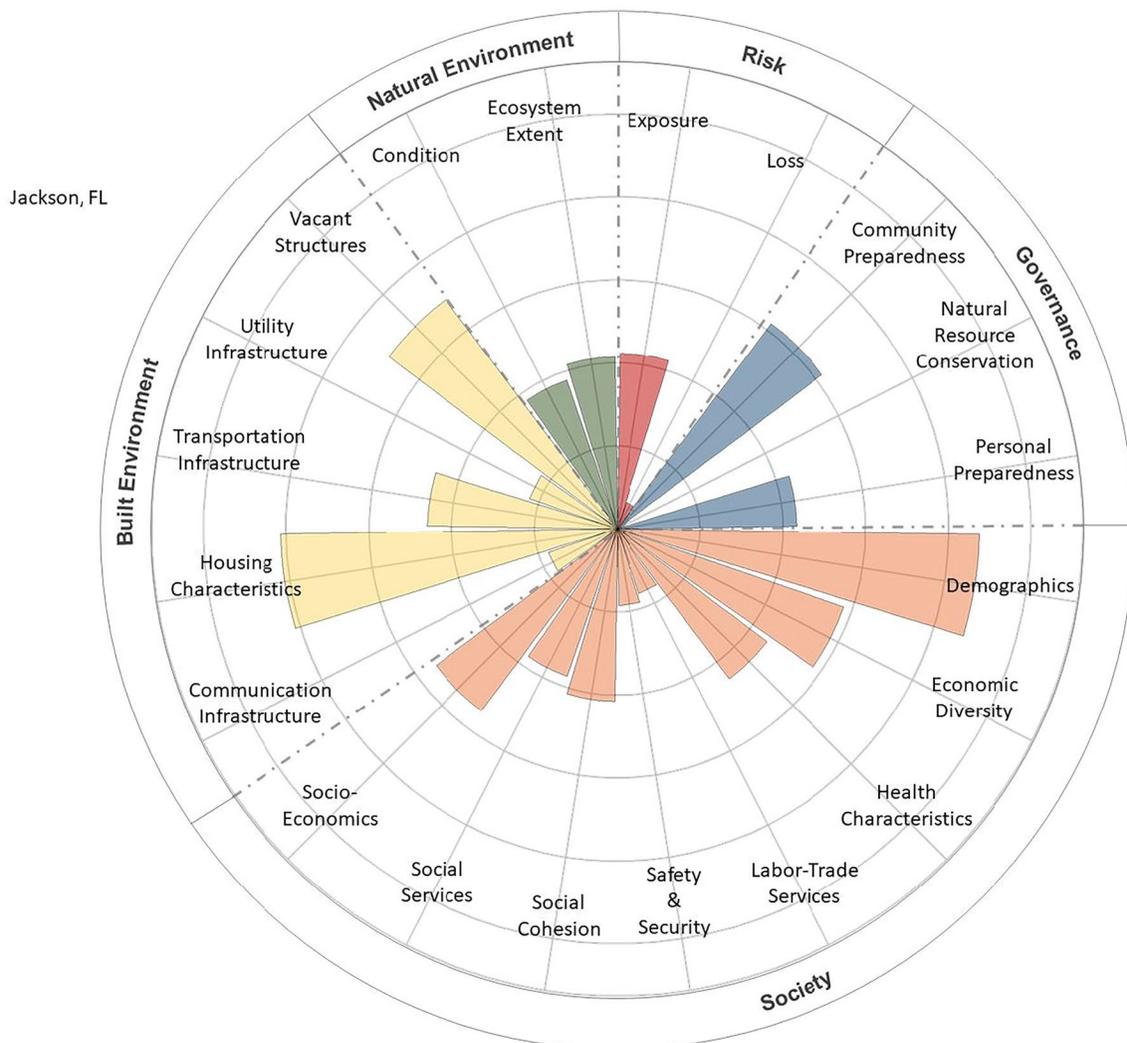
Figure 4. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to Jackson County, Florida domain scores.

and 2.0. While all 21 parishes are vulnerable with relatively low resilience, several are characterized by low built environment, natural environment, or society domain scores suggesting stronger tendencies to slower recovery rates.

East Baton Rouge, Ascension, Livingston, and Tangipahoa parishes were the most affected by the 2016 flooding event (Meyer et al., 2020). In East Baton Rouge Parish, a very low score for the natural environment domain (unusual for Louisiana) suggests high levels of impervious surfaces resulting in very low environmental extent scores (Figure 5), adding low recovery potentials to high vulnerability (i.e., risk = 0.666 nearly three times the national risk average). While Ascension Parish shows slightly higher recoverability potential, the parish's extremely high-risk score (0.907 or almost four times the national average risk) coupled with only an average governance score results in basic low-level resilience (Table 5). Livingstone Parish also shows high risk and relatively low governance but, while its built environment score is about average, the parish's infrastructure scores for communications and transportation are very low, suggesting standard pre-event warning systems (Figure 5, number of mobile and paging towers and television infrastructure are in the nation's bottom 10%) and low event evacuation potential (arterial road structure and high access roadway provide low probability of easy pre-event evacuation). Recovery potential for Livingston Parish is also reduced by standard social services and labor-trade services scores (Figure 5) driven by low numbers of emergency shelters, hospitals, and blood banks

Table 5
Cumulative Resilience Screening Index (CRSI) and Domain Scores for Select Counties in Louisiana Parishes Associated With the Path of 2016 Louisiana Flood

County	Risk	Governance	Basic resilience	Built environment	Natural environment	Society	CRSI
Acadia	**0.271**	**0.535**	**1.974**	0.493	0.496	**0.480**	**2.915**
Ascension	**0.907**	**0.584**	**0.644**	0.461	0.429	0.558	**0.889**
Avoyelles	**0.316**	0.617	**1.953**	0.445	0.508	**0.472**	**2.668**
East Baton Rouge	**0.666**	**0.553**	**0.830**	0.589	**0.354**	0.588	**1.325**
East Feliciana	**0.265**	**0.566**	**2.136**	**0.364**	**0.371**	**0.363**	**1.270**
Evangeline	**0.257**	**0.554**	**2.156**	**0.359**	0.480	**0.421**	**2.070**
Iberia	**0.360**	**0.506**	**1.406**	0.399	0.429	**0.454**	**1.417**
Iberville	**0.524**	0.605	**1.155**	0.427	0.448	0.584	**1.600**
Jefferson Davis	**0.314**	**0.508**	**1.618**	0.403	0.485	**0.477**	**1.949**
Lafayette	**0.655**	**0.564**	**0.861**	0.596	0.437	0.588	**1.564**
Livingstone	**0.515**	**0.553**	**1.074**	0.495	0.423	**0.495**	**1.392**
Pointe Coupee	**0.352**	0.609	**1.730**	0.434	0.465	0.537	**2.348**
St. Helena	0.206	**0.566**	**2.748**	**0.364**	**0.371**	**0.363**	**1.305**
St. Landry	**0.261**	**0.553**	**2.119**	0.547	0.481	0.510	**3.488**
St. Martin	**0.345**	**0.511**	**1.481**	0.416	0.437	0.529	**1.814**
St. Tammany	**0.698**	**0.410**	**0.587**	0.597	0.423	0.518	**0.968**
Tangipahoa	**0.404**	**0.569**	**1.408**	0.573	0.422	**0.438**	**2.005**
Vermilion	**0.350**	0.653	**1.867**	0.500	0.467	**0.443**	**2.519**
Washington	**0.254**	**0.302**	**1.189**	**0.348**	0.441	**0.371**	**0.882**
West Baton Rouge	**0.596**	**0.584**	**0.980**	0.451	0.487	0.691	**1.721**
West Feliciana	**0.314**	0.712	**2.268**	**0.370**	**0.409**	**0.490**	**2.169**

Note. Bold denotes significantly below the national average for CRSI, below the national averages for all domains except risk which denotes above the national average, and below the national average for basic resilience.

(lower 10% nationally) as well as low numbers of construction workers (framers, masons, and roofers) to assist in rebuilding.

Similarly, Tangipahoa Parish has a lower level of communication infrastructure to aid with evacuation responses and lower classes of social services and labor-trade services to aid in recovery. In addition, Tangipahoa Parish also has a lower level of personal preparedness for natural hazards, with its residents having very low levels of flood insurance protection. While a CRSI assessment would depict all 21 parishes as highly vulnerable to a major flooding event like the 2016 mid-state flood, it also shows Ascension, East Baton Rouge, Livingstone, and Tangipahoa Parishes as very vulnerable to such an event with reasonable long recovery periods following the event. Additionally, the CRSI assessment suggests that Washington Parish, while having lower risk, also has very low governance, built environment, and society domain scores (Table 5), making recovery from an event (if it occurs) very slow. Similarly, Saint Tammany Parish has low levels of governance, making that parish vulnerable to these types of events driven by lower levels of community preparedness (e.g., percent of Small Business Administration recovery funds spent on hazard mitigation) and personal preparedness (e.g., number of National Flood Insurance Program participants).

3.4. Western Wildfires (2016–2018)

Unlike hurricanes and inland flooding, wildfires are natural hazards that generally are county-specific, making a comparative examination of a single wildfire event (i.e., comparison of counties) impossible. One wildfire event in 2016–2019 had spatial expanses of two counties (i.e., Thomas Fire in 2017 impacting Ventura and Santa Barbara Counties, CA). The Clayton Fire (2016) burned 3,929 acres in Lake County, CA, destroying 300 build-
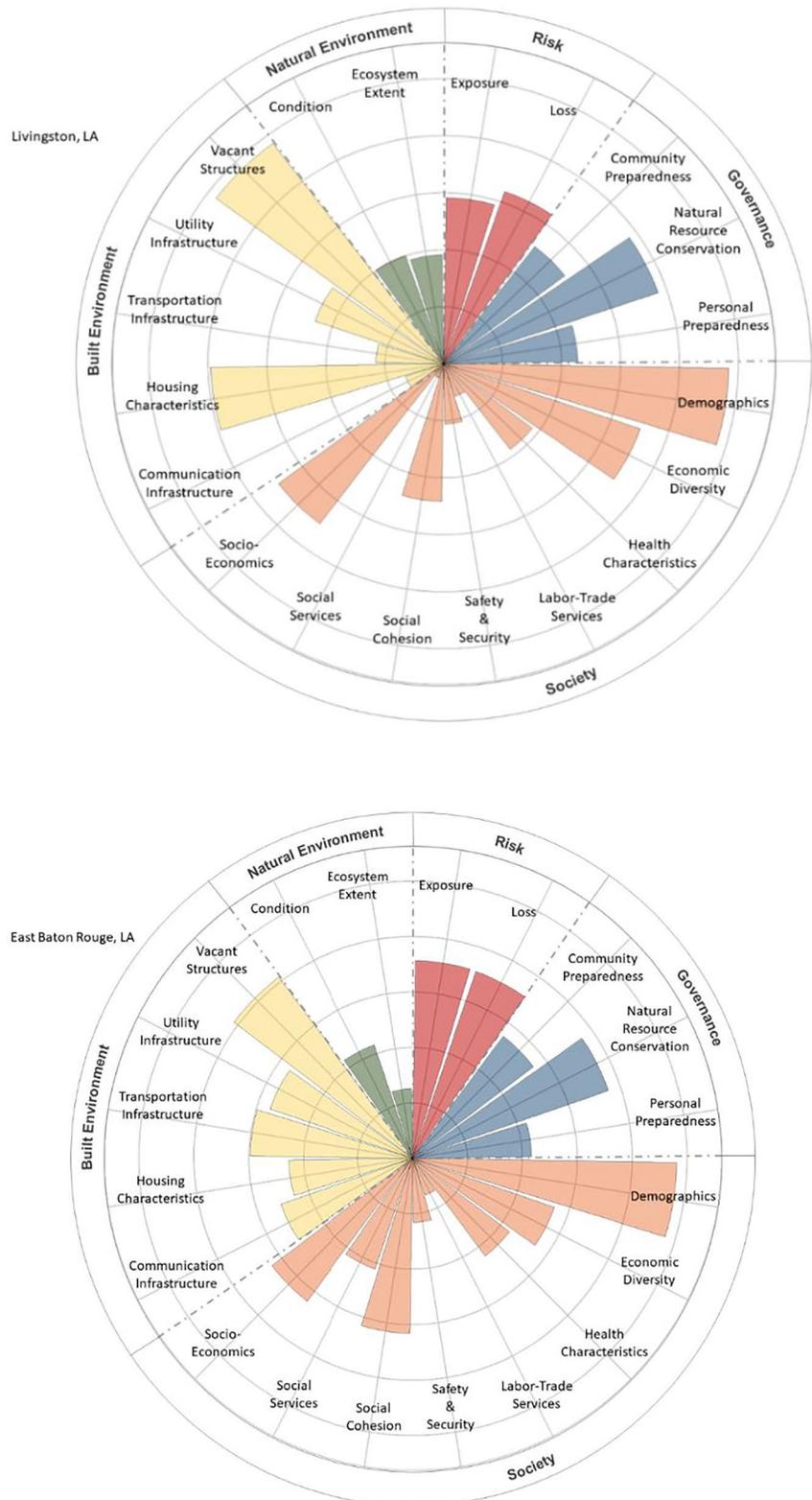
Figure 5. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to domain scores for East Baton Rouge and Livingstone Parishes, Louisiana.

Table 6
Cumulative Resilience Screening Index (CRSI) and Domain Scores for Select Counties in California Associated With Wildfires in 2016–2019

County	Risk	Governance	Basic resilience	Built environment	Natural environment	Society	CRSI
Butte	0.211	**0.484**	**2.293**	0.721	0.414	**0.397**	**3.938**
Lake	0.160	**0.195**	**1.219**	0.490	0.552	**0.360**	**1.676**
Santa Barbara	0.224	**0.556**	**2.482**	0.830	0.645	0.559	7.179
Ventura	**0.384**	**0.534**	**1.391**	0.751	0.660	0.550	**3.766**

Note. Bold denotes significantly below the national average for CRSI, below the national averages for all domains except risk, which denotes above the national average, and below the national average for basic resilience.

ings before it was contained. The Camp Fire (2018) was the most destructive and deadliest in California history (Baldassari, 2018). The fire caused at least 85 civilian fatalities, covered over 15,300 acres, and destroyed over 18,000 structures but occurred in a single county (Butte County, CA).

The Thomas Fire in 2017 burned over 280,000 acres and destroyed over 1,000 homes, with many of them in Ventura County, CA. Three weeks later, this fire was followed by the Montecito flooding and debris flows which devastated Santa Barbara and Ventura Counties. Examination of the CRSI scores for these two counties shows a vast difference between them (7.179 for Santa Barbara and 3.766 for Ventura), suggesting that Ventura County might exhibit lower resilience than Santa Barbara County (Table 6). The primary difference in the domain scores for the two counties is that the risk domain for Ventura County is about 70% higher than Santa Barbara County. While their governance scores are below the national average, they are relatively high (i.e., >0.5). The built environment score for Santa Barbara County is somewhat higher than that of Ventura County. The scores for these counties suggest that Ventura County might be more vulnerable to natural hazards than Santa Barbara County but that the recovery potential for both counties is about equal.

About one-third of the residents of these two counties speak Spanish at home, and Spanish-speaking residents lacked general information about the wildfire. Initially, emergency warnings were only available in English (CAUSE, 2018). Thus, information about road and school closures, evacuation routes, area shelters, drinking water safety, and air quality was unavailable to one-third of the residents. The wildfire closed the major thoroughfare between Ventura and Santa Barbara County (Highway 101), making commuting to jobs in Santa Barbara County more difficult from Ventura County where housing was more affordable. These observations support a higher impact and poorer resilience in Ventura County than in Santa Barbara County, as suggested by the CRSI results (Figure 6).

The Clayton and Camp Fires were very different from the Thomas Fire. Both fires burned in north-central California, generally away from highly populated areas and in areas with lower proportions of agriculture and business. Lower levels of governance describe both counties, particularly Lake County, which is 67% below the national average, with the percent of Small Business Administration recovery funds spent on hazard mitigation being among the lowest in the country and the land protection priority index for preserving biodiversity in the lower 5% of the US. While the risk-domain score is not exceptionally high (0.160), the low level of governance (0.195) results in a situation where the county is not very resilient if a hazard occurs. Many social indicators suggest extended recovery times for this county if an event occurs, with scores for safety and security, labor-trade services, and social services all being relatively low (Figure 7). The number of emergency, civil, public safety, and outpatient services per 100,000 residents is among the country's lowest 10%, making a recovery from an event and pre-planning for evacuation and community preparedness for an event difficult.

The Camp Fire in 2018 represents a different type of governance issue. Residential development in wildland-urban interface areas such as Paradise, CA (in Butte County), is considered a state responsibility area (i.e., California provides prevention and suppression strategies and programs). These programs require financial resources, and a special fee was imposed on property owners in 2011 for prevention. However, the programs were unpopular and were suspended, and the fees were repealed in 2017. Despite years of fuel reduction programs, multiple wildfires occurred in the county. Investigations found that PG&E (Pacific Gas and Electric Company) power line failures during high winds accounted for many fires. Studies after the Camp Fire by the California Public Utilities Commission determined that failed utility infrastructure (over 900 problems with towers and other equipment)
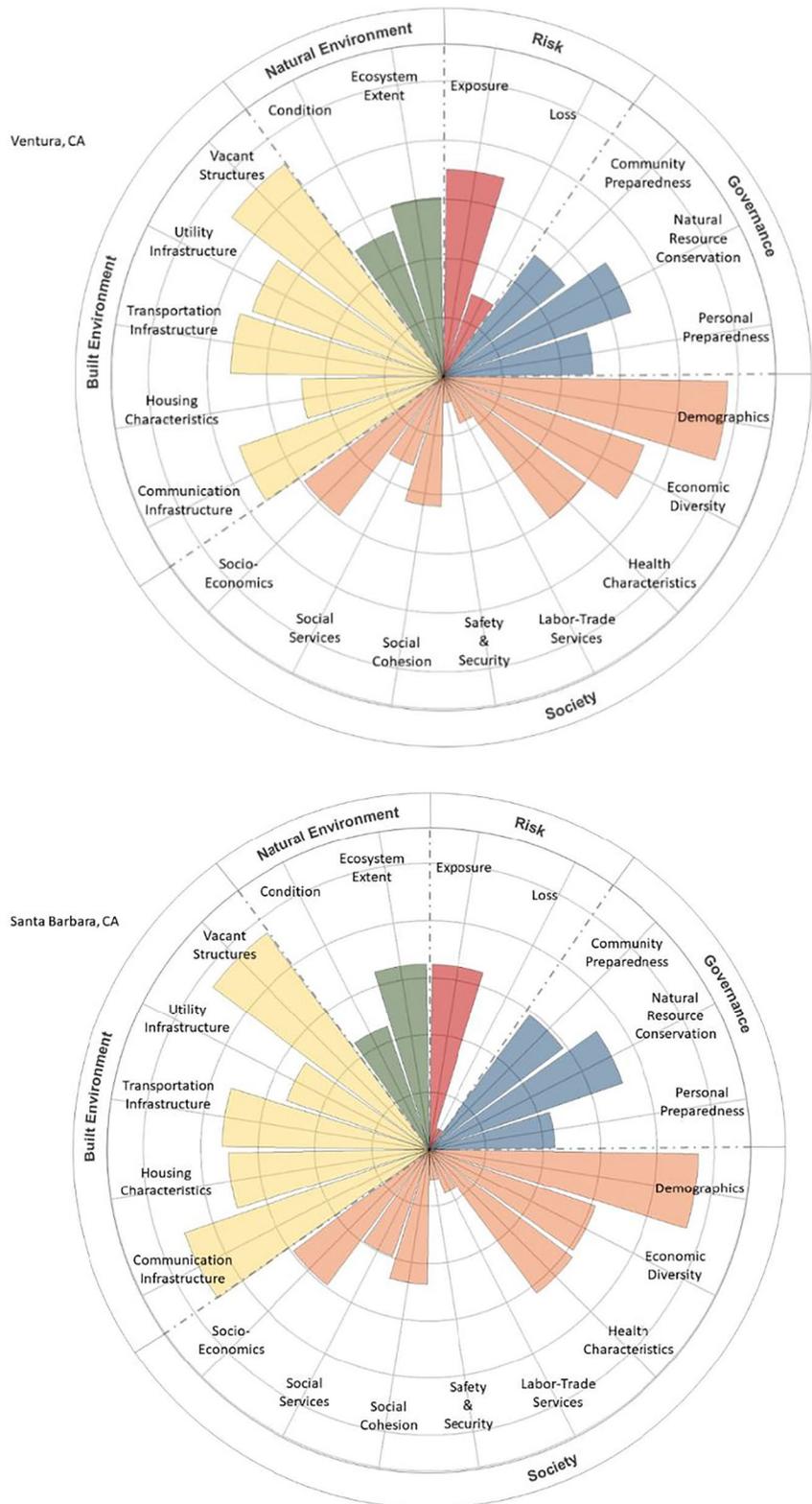
Figure 6. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to domain scores for Santa Barbara and Ventura Counties, California.
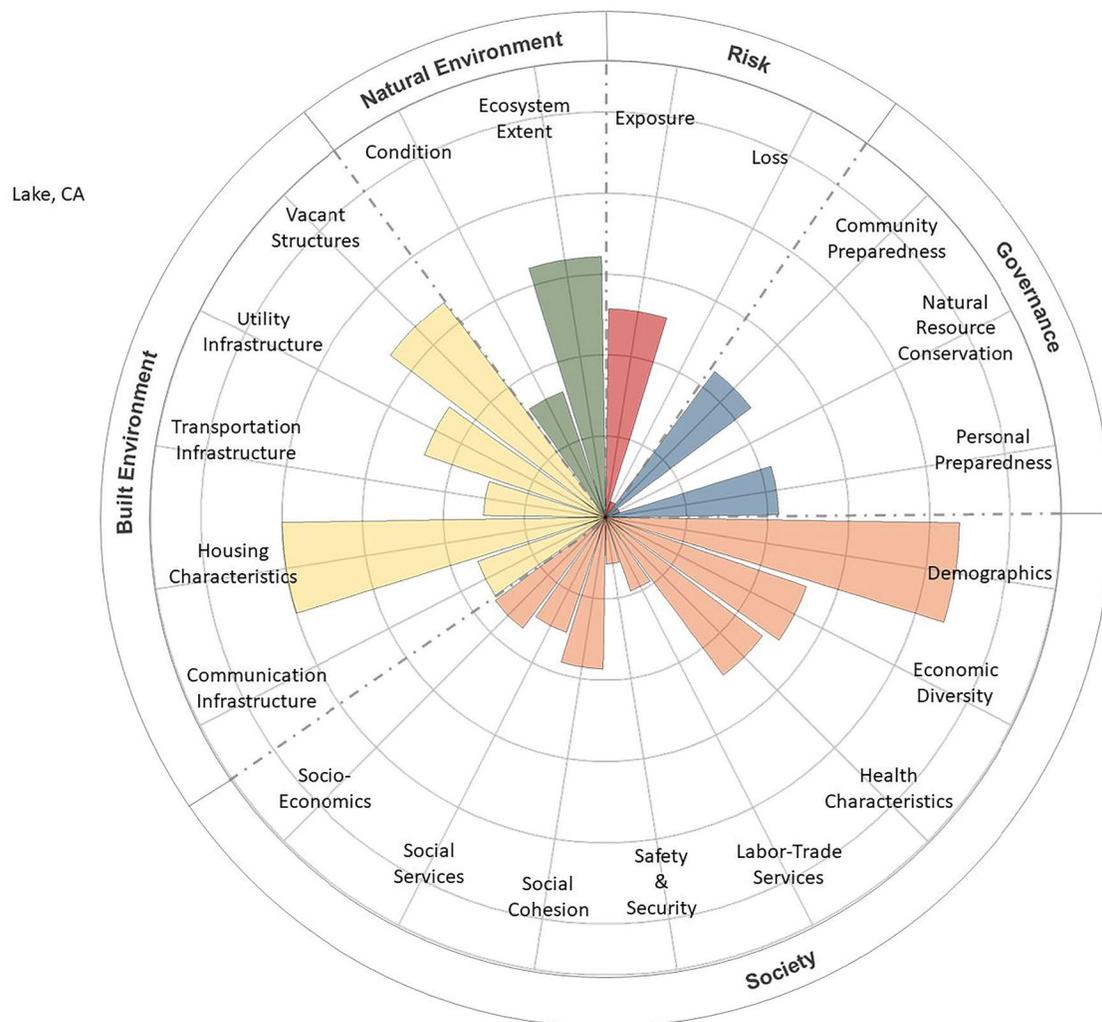
Figure 7. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to domain scores for Lake County, California.

caused the Camp Fire. While the CRSI results (Table 6) suggest Butte County has lower than average risk accompanied by lower than average governance, the overall CRSI score is a little below average. The domain scores indicate that the occurrence of an event was not exceptionally high, but, should an event occur, recovery would be slowed by multiple societal factors, including the number of emergency shelters and public safety services per 100,000 residents (Figure 8). Unfortunately, CRSI does not include public or private negligence information. While CRSI shows that Butte County would be slow to recover from a natural hazard, the likelihood of such a hazard occurring would not be exceptionally high.

4. Conclusions

Observational verification of models and indices provides users with observational, but non-statistical, confidence in their tools for decision-making and evaluations. Using hurricanes, inland flooding, and wildfires, the general accuracy of processes driving the CRSI results has been demonstrated using natural hazard risk information taken from outside the period used for the index construction. Further verification, structurally and functionally, can be achieved by examining the ability of the CRSI domains to identify likely hot spots and trending spatial locations for risks and governance and the recoverability domains—social, built, and natural environment. All models and indices developed for use by decision-makers should undertake this type of verification or a similar validation operation to enhance user confidence.
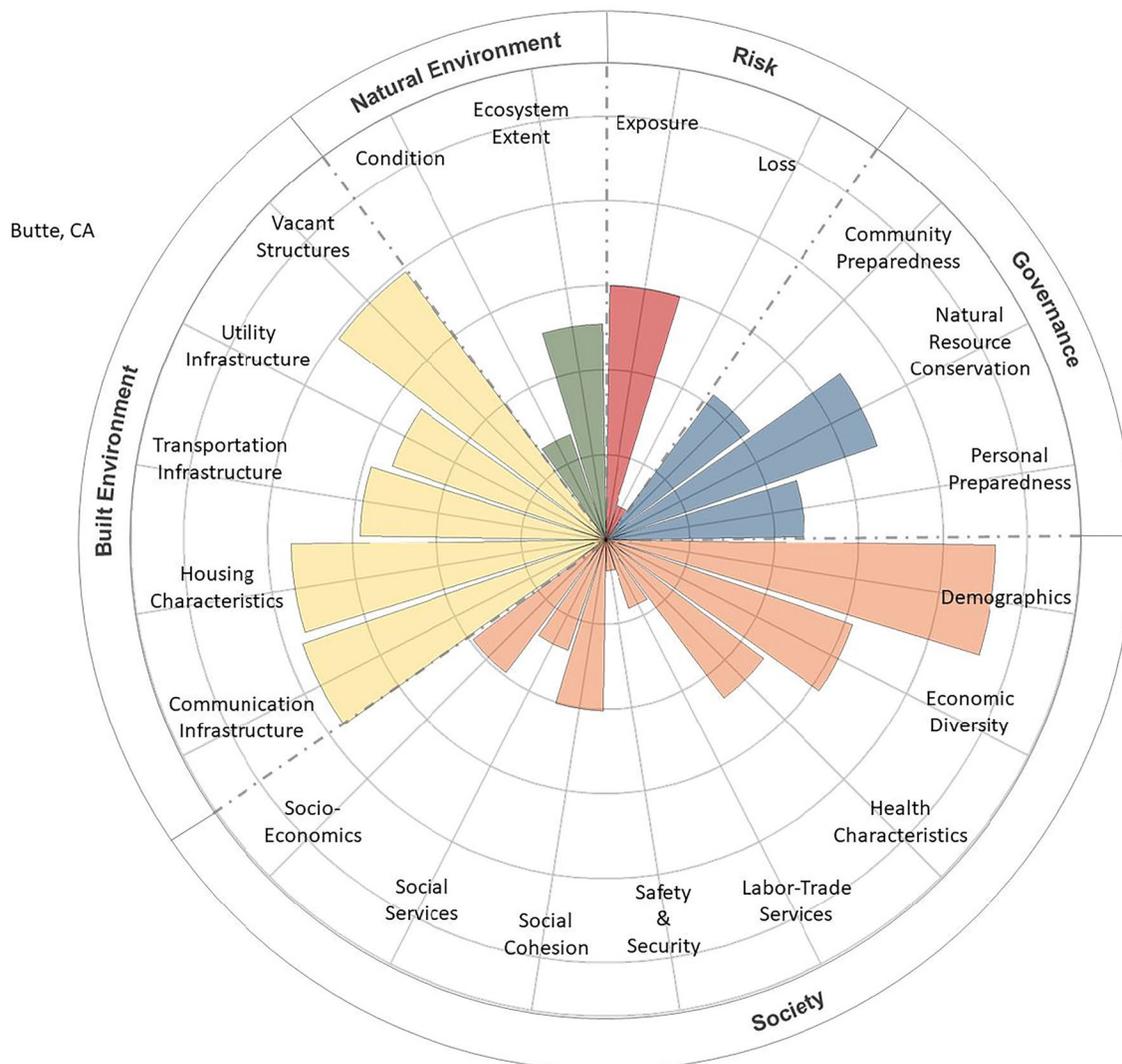
Figure 8. Polar plot of the relative contributions of Cumulative Resilience Screening Index indicators to domain scores for Butte County, California.

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Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The metadata and data associated with this manuscript are available through the U.S. Environmental Protection Agency's Science Inventory and the ScienceHub. The Science Inventory (http://cfpub.epa.gov) and ScienceHub (https://catalog.data.gov) are searchable databases for research products completed primarily by EPA's Office of Research and Development. These locations are general repositories required through EPA for manuscripts

(Inventory) and data generated by EPA (ScienceHub) and require some searching for specific data sets. The data set used in this manuscript is primarily non-EPA data taken from the internet and combined in a new way to form CRSI. The specific data for the CRSI information used in this manuscript can be located at the following site: https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7B14C64E6B-79AE-4C03-8F14-72E1E51A7D15%7D (EPA Environmental Data set Gateway).

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