Agricultural and Resource Economics Review (2025), 1–28
doi:10.1017/age.2025.17

RESEARCH ARTICLE

Creating the Comprehensive Community Vulnerability Index

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(Received 30 June 2024; revised 3 February 2025; accepted 24 February 2025)

Abstract

This study quantified the relative vulnerability of 3,141 counties in the United States. We built a comprehensive community vulnerability index (CCVI) that considers household, business, and public levels. Eighteen variables related to household socioeconomic characteristics, business size and diversity, local government economic size, social capital, and net immigration were used. In the existing vulnerability indices (CRE, SVI, and SoVI), the indices were constructed by using socioeconomic characteristics of the household. In addition to socioeconomic variables, this study sought to expand the concept of "place-based" by considering the business structure within the community and the potential ability to maintain the existing order of the community to construct a comprehensive index. Additionally, by providing the relative vulnerability of the community at each level (private, business, public), each dimension can provide evidence on which areas are more vulnerable and need remediation than others. We expect that the CCVI can be broadly extended to be used in various forms. In this study, we extend the vulnerability index by including exogenous variables such as climate change. In particular, the extended climate-enhanced CCVI in this study shows that the existing vulnerability index can be strengthened by incorporating extreme climate events.

Keyword: Comparative analysis; comprehensive community vulnerability index (CCVI); principal component analysis (PCA); resilience; vulnerability

JEL codes: R11; R12

Introduction

The community in which we live can be affected by a variety of external shocks, such as natural disasters, economic crises, and financial shocks. Empirical studies have been conducted on the increase in the frequency and intensity of various natural disasters due to climate change, and the frequency and scale are expected to become increasingly stronger (Van Aalst, 2006; Banholzer et al., 2014; Coronese et al., 2019). As these threats increase in scale and urgency, communities are likely to suffer direct property damage and could have long-term negative impacts on the entire local economy. Furthermore, communities may differ in their response to exogenous shocks, such as unexpected financial crises or human-caused illnesses. We focus our research on identifying indicators that make communities more vulnerable to external shocks. As part of early risk management research focusing on external shocks, physical concepts and systems of social vulnerability were often emphasized, along with infrastructure and technology. However, in recent years, the concept of social vulnerability has been extended to include economic and social factors that affect community resilience as part of risk management (Juntunen, 2005). In this context, organizations such as the Centers for Disease Control and Prevention (CDC) and the Pacific Research Institute are measuring social vulnerability according to various variables and topics (external stress, climate change) by measuring vulnerability indices targeting only the private sector or limited areas[1] (CDC 2022; Pacific Research Institute, 2012).

In similar ways, various indices have been developed to assess the vulnerability of local communities by incorporating a comprehensive set of variables that reflect the socioeconomic status and household characteristics of populations. These indices measure regional vulnerability using information on individuals and households from the American Community Survey (ACS) and related demographic data. In particular, the CDC Social Vulnerability Index (SVI) and the US Census Bureau's community resilience estimates (CRE) focus on developing tools to identify the socioeconomic vulnerability of population groups, which are widely used to measure local vulnerability (CDC 2022; U.S. Census Bureau, 2021b). However, rather than evaluating the accuracy of these existing vulnerability indices, we propose a conceptual expansion. This study attempts to expand the concept of existing indices that measure vulnerability primarily using "people-based" statistics that can be obtained from individuals and households to include "place-based" factors that contribute to vulnerability.

This study emphasizes the need to develop a more comprehensive vulnerability index that can identify the degree of vulnerability of individuals and businesses within a community to disturbances or changes in the context of comprehensive shock management that can affect the community and aims to develop a comprehensive community vulnerability index (CCVI) that can be applied to all counties in the United States. As part of the research structure, we review existing vulnerability indices and discuss the conceptual extension of CCVI. We then explain the data and implementation method for this and discuss the results of index construction and validation.

Reviewing existing indices: strengths and gaps

This section introduces the objectives and characteristics of existing indicators that identify community vulnerability from various perspectives, summarized in Table 1, and explains the background and conceptual extension of the CCVI proposed in this study.

First, the CRE developed by the US Census Bureau is an index that measures the vulnerability and resilience of a specific population group and measures the ability of individuals and households to prepare for and recover from disasters (Bradatan et al., 2023). It uses individual and household information from the ACS and the Census Bureau's Population Estimation Program (PEP), and the variables, calculation methods, and methods of representing vulnerable areas used to construct the index are based on data

[1]Pacific Research Institute's Social Vulnerability to Climate Change is a census-track level index that measures vulnerability to climate change in California. The index uses private-level (individual or household) data such as socioeconomic factors and housing conditions and measures vulnerability to external shocks such as climate change scenarios, extreme heat, air, and sea level rise.

https://doi.org/10.1017/age.2025.17

Table 1. Summary of existing social vulnerability indices

	CRE	SVI	SoVI	NRI
Full title	Community resilience estimates	CDC/ATSDR Social Vulnerability Index	Social Vulnerability Index for the United States	National Risk Index
Agency	US Census Bureau	Centers for Disease Control and Prevention (CDC)	University of South Carolina Hazards & Vulnerability Research Institute	Federal Emergency Management Agency
Objective	Community resilience	Social vulnerability	Social vulnerability	Risk
Hazards/ risk included	No	No	No	Yes
Description	CRE quantifies the ability of individuals and households within a community to prepare for and recover from disasters.	SVI measures the vulnerability of a community, helping emergency response planners and health authorities identify and triage communities most in need of support before, during, and after a hazardous event.	SoVI measures social vulnerability to environmental hazards in US counties. This index is a comparative indicator that helps examine differences in social vulnerability across counties.	NRI shows the potential vulnerability and resilience of a community based on the expected damage scale of 18 natural hazards.
Variables and categories	11 socioeconomic factors No categories	15 socioeconomic factors 4 Categories - Socioeconomic status -Household composition - Race/ethnicity/ language -Housing/ transportation	29 socioeconomic factors 8 categories - Wealth - Race and social status - Age - Ethnicity and lack of health insurance - Special needs populations - Service sector Employment - Race - Gender	3 categories - Expected annual loss - Social vulnerability - Community resilience
Recent release year	2022	2022	2019	2021
Result	Rate of individuals with components of social vulnerability	0 to 1 scale (percentile)	*Z*-score	Risk score $=$ $EAL \times f\left(\frac{SV}{BRIC}\right)$
Coverages	County/census tract	County/census tract	County	County/census tract
Update interval	1 year	2 years	Unknown	Unknown

https://doi.org/10.1017/age.2025.17

and modeling published by the US Census Bureau. The main variables used in the CRE are 11 core vulnerability factors[2] that affect resilience in terms of social, economic, and health aspects.

The CRE classifies vulnerability status by calculating the percentage of 0, 1~2, or 3 or more of the 11 vulnerability factors (vulnerability status is classified as a binary choice based on a set threshold). Although it is difficult to immediately determine which parts of an area classified as vulnerable are clearly vulnerable, it has the advantage of quickly identifying areas that exceed the threshold among the 11 vulnerability factors, thereby supporting rapid policy decisions. It also provides a higher resolution index by identifying vulnerabilities at both the census tract level and the county level, representing superior accuracy in measuring the vulnerability (Willyard et al., 2022).

Second, the SVI from the CDC and the Agency for Toxic Substances and Disease Registry (CDC/ATSDR SVI or SVI) helps identify vulnerable populations and provide focused aid (CDC, 2022). By using a comprehensive data source, the SVI integrates US Census data that covers a wide range of social factors, including social factors such as poverty levels, unemployment levels, age distribution, disability status, and education levels. It provides a detailed view of vulnerability by providing data from the county level to the census tract level. Specifically, the SVI integrates 15 social factors and groups them into four categories: socioeconomic status, household composition and disability, minority status and language, and housing type and transport. It also provides a detailed score for each group. The index is also easily accessible and frequently utilized by public health experts and policymakers because of its simple and easily applicable scoring system, which scores locations from 0 (most vulnerable) to 1 (most vulnerable). It is particularly useful for emergency preparedness and response planning and helps to identify areas where resources should be invested before, during, and after a disaster.

The third index, the SoVI was developed by the Risk and Vulnerability Institute at the University of South Carolina. The purpose of this index is to evaluate the social vulnerability of US counties to environmental disasters (HVRI, 2019). The SoVI expands vulnerability analysis to 29 variables and provides a more detailed and nuanced view of social vulnerability through the use of more variables. It captures a broader range of socioeconomic and demographic factors, making it valuable for academic and policy research where depth is important (Tarling, 2017). Unlike the fixed structure of the CDC SVI, the SoVI uses principal component analysis (PCA) to dynamically group variables into factors to reflect current social conditions and evolving vulnerabilities, and the SoVI better identifies geographic outliers and unique areas of vulnerability within a region. Therefore, SoVI, which uses multiple variables to measure vulnerability, is more effective in pinpointing specific neighborhoods that may need targeted interventions. Although PCA has the great advantage of covering a wide range of data, it is not easy for nonexperts to understand and use (Tarling, 2017).

Lastly, the Federal Emergency Management Agency created the National Risk Index (NRI), a measurement tool used to evaluate community risk from natural disasters across the United States. The NRI is intended to give communities a thorough grasp of disaster risk and to assist them in planning for, responding to, and recovering from natural disasters. The index integrates three broad categories, which are the expected annual loss (EAL), social vulnerability, and community resilience, to provide a comprehensive risk score for each area. First, the EAL is an estimate of economic, social, and human losses

[2]The variables for measuring vulnerability in the CRE are as follows: income-to-poverty ratio, single or zero caregiver household, crowding, communication barrier, households without full-time, year-round employment, disability, no health insurance, age 65+, no vehicle access, and no broadband internet access.

https://doi.org/10.1017/age.2025.17

from a natural disaster on an annual basis. The characteristics of this index are that it directly reflects risk by measuring the frequency of occurrence, disaster intensity, and scope of impact of 18 natural disasters, such as floods, hurricanes, earthquakes, droughts, and wildfires, which can be actual exogenous variables. Next, social vulnerability measures the possibility that a specific population group will be more affected by a disaster and, like other indicators, includes population characteristics. The last component of the NRI, community resilience, evaluates the ability of a community to adapt to and recover from a disaster situation and measures institutional capacity such as local government resources and the presence of an emergency response system, as well as economic stability and community preparedness.

The NRI also has the strength of assessing risk at the county and census tract levels, allowing for the development of disaster response plans tailored to local characteristics. Because the impact of disasters is directly included in the index, areas classified as NRI vulnerable may show different distributions than vulnerable areas classified in other existing indices.[3] In addition, although the index directly includes risk aspects such as exogenous shocks and natural disasters, the NRI's EALs reflect the characteristics of a multi-hazard approach and generalized risk assessment methods that aggregate the overall risk factors of each disaster type and express them as a single indicator. Therefore, additional loads may be required to observe damage and vulnerabilities related to specific disasters.

In general, the NRI is designed to assess risk from natural disasters based on the potential negative impacts of such events, considering expected losses, social vulnerability, and community resilience. In contrast, the CCVI pursued in this study specifically measures vulnerability at three levels: private, business, and public. This approach is different in its sub-objectives, as it allows for a more nuanced analysis that considers vulnerability at the individual household, economic structure, and aggregated public level data and potentially provides a more detailed view of how vulnerability is distributed within a community. In summary, the NRI provides a holistic view of risks associated with natural disasters and emphasizes the trade-off between risk impacts and community resilience, whereas the CCVI focuses on a detailed analysis of vulnerabilities across three key levels within different community segments. This approach extends the socioeconomic component vulnerability measures of existing vulnerability indices (CRE, SVI, SoVI) to enable targeted interventions that address specific vulnerabilities inherent in the economic structure and public sector within a community.

Comprehensive community vulnerability index

The prospect of creating a "comprehensive" community vulnerability index is technically impossible. This is partly due to the reality that community vulnerability can be such a subjective term. One person's concept of vulnerability can be much different than their

[3]The NRI risk score, as shown in the eighth item "Result" in Table 1, is calculated as the product of the expected annual loss (EAL) and the community risk factor (CRF). The EAL represents expected damage from exogenous shocks measured across 18 disaster types, while the CRF is modeled as a triangular distribution function based on social vulnerability and community resilience. Although the NRI risk score does not explicitly weight EAL, it is heavily influenced by it. According to the National Risk Index Technical Documentation, when the EAL, social vulnerability, and community resilience are measured as 99.87, 37.43, and 78.36 for County A, and 99.51, 73.07, and 70.85 for County B, respectively, the resulting risk scores are 99.55 for County A and 98.31 for County B. This demonstrates that, despite incorporating social vulnerability and community resilience, the risk score is largely driven by the EAL.

https://doi.org/10.1017/age.2025.17

neighbor's concept. Further, as our communities become more interconnected with their physical, economic, social, and environmental systems, areas of vulnerability emerge that may not have previously existed or, at least, have not been considered in the past.

While this paper uses the term "comprehensive," it is meant more to expand the breadth of how we construct indices used to measure vulnerability as opposed to trying to include every dimension of community vulnerability that exists in the literature.

This research draws from the Comprehensive Wealth Framework (CWF) highlighted in concepts of Rural Wealth Creation (Johnson et al., 2014). CWF complements the community capitals paradigm (cf. Emory and Flora, 2006). Similarly, it identifies a collection of "wealths" (physical, financial, natural, human, intellectual, social, cultural, and political). CWF highlights the concept of Fisherian income (Nordhaus, 2000). Basically, the income of a region is measured by the flow of services generated from the assets of the community. Consequently, the wealth of a community then is a measure of the level of these assets.

Unfortunately, many of these assets have attributes that make them difficult to measure because they may not otherwise have a market to generate a market price. Other assets may be intangible and hard to quantify. As a result, we are often left with measuring the "flow" of the service, or even less, an outcome on people and businesses as a result of that flow.

One of the strengths of CWF is that it identifies attributes of wealth assets. For example, CWF distinguishes people-based assets from place-based assets. This is analogous to the difference between gross domestic product (GDP), which is place-based, and gross national product or gross national income, which is people-based. For example, communities benefit from the stock of housing in a community even if it is unoccupied because that stock can be leveraged for people living in it in the future. Further, businesses that are owned by nonresidents still provide property taxes on buildings and equipment they own in a community. Consequently, a vulnerability index that includes only indicators that are "people-focused" misses place-based elements that contribute to vulnerability/resilience.

Further, Johnson, Raines, and Pender distinguish between public wealth and private wealth. A part of people-based wealth includes their portion of the public's wealth as residents of a political jurisdiction. As a result, investments in infrastructure and related emergency preparedness help to reduce vulnerabilities. Due to the place-based and public attributes of community wealth, this index adds to many of the people-based indices of social vulnerability, business, and public sector dimensions.

In summary, our research seeks to expand the conceptual framework of existing vulnerability indices like the CDC's SVI and the SoVI, which primarily focus on predefined sets of social and economic variables. Instead of directly including exogenous shocks (risks) like those applied in the NRI, our index integrates aspects of vulnerability at the household, business, and public levels. This approach allows for a more nuanced understanding of vulnerabilities that encapsulate both business operations and public infrastructure and provide a novel expansion in the concept of community vulnerability. This integration process and the method of specifying the index are introduced in the next section.

Data and specification

This study requires three categories of data: private (household) level data, business-level data, and public-level data to construct the CCVI. The reason for constructing the index using three dimensions of data (household level, business level, and public level) is that this study recognizes and focuses on the multifaceted nature of community vulnerability. Household-level data provides information on the socioeconomic status, demographic characteristics, and living conditions of individuals and households, which serve as the fundamental units of a community. This data helps assess the ability and vulnerability of individuals and families to respond to various stressors and external shocks. Therefore, the household-level approach is important as it allows for a more granular analysis of the community units that are most immediately and directly impacted by the vulnerabilities of the county. This paper finds that using business-level data is essential in terms of focusing on economic activity within a community, including industry structural diversity and size. This information is crucial to determine a community's economic stability, resilience, and adaptability with respect to external shocks or disruptions. It also helps in measuring the economic adaptation capacity of the community and the vulnerability of the economy and the local industries. Public-level data gives a broader perspective on a community's capability to support residents and businesses and sustain social order in terms of external shocks. At the public level, data such as local government expenditure can be a critical factor in determining a community's potential ability to respond to and recover from the adverse effects of a crisis. Integrating these three categories of data can provide a holistic view of community vulnerability, encompassing economic and social dimensions to external shocks.

The CCVI has 18 indicators, each with three levels, with a higher index value indicating higher vulnerability. The cardinal direction (+/– sign) was adjusted according to the characteristics of each variable. For example, regions with a high business-level entropy index (having high diversity) are considered less sensitive to the effects of external shocks, and their CCVI is low. Therefore, variables whose cardinal directions were opposite to the concept of vulnerability were adjusted to fit the logic of this study. Below is a detailed description of the three data categories, and a summary table of the data[4] used is included at the end of this chapter (see Table 2). To construct the CCVI, we set the base year of the index to 2020 and apply the data at each level accordingly.

Private (household) level

To capture vulnerability at the household level, data surveying the social and economic status of households in the community are required. Although there are indices from other research institutes that have been designed to assess social vulnerability at the household level, they conduct vulnerability analysis for limited areas or specific disasters. Therefore, this study explored an index that could be used universally across the United States and represents vulnerability at the household level. Candidates that could be used included the SVI, which was constructed by the CDC based on household-level American Community Survey data targeting communities across the United States, and the CRE from the Census Bureau in the United States. This study directly uses CRE to measure the household-level component of the CCVI for the following reasons.

First, CRE is an established methodology that does not focus on specific exogenous shocks in terms of data comprehensiveness (U.S. Census Bureau, 2022). CRE is suitable for building a composite index because it includes general and universal indicators that are important for assessing household resilience, such as poverty level, age distribution, disability status, housing type, vehicle accessibility, and health insurance status. Specifically, CRE sets 10 vulnerability variables[5] at the household level, such as

[4]A total of 18 variables were selected to construct a CCVI. All variables were normalized using Z-score, percentile rank. Also, variables are scaled according to the population or total GRP of the county to facilitate homogeneous comparisons between counties.

[5]The social vulnerability components of CRE are tabulated in the Appendix.

https://doi.org/10.1017/age.2025.17

Table 2. Summary of data used to construct comprehensive community vulnerability index

Private (household) level			
Categories	Variables	Sign[1]	Description[2]
Community resilience estimates[3] (CRE)	Poverty ratio	+	Income poverty ratio < 130% (HH)
	Single or zero caregiver household	+	Only one or no individuals living in the household who are 18–64 (HH)
	Crowding level per room	+	Unit-level crowding with > 0.75 persons per room (HH)
	Communication barrier	+	Limited English-speaking households (HH) or no one in the household with a high school diploma (HH)
	Job status	+	No one in the household is employed full-time, year-round (HH)
	Disability	+	Disability posing constraint to significant life activity (I)
	Insurance status	+	No health insurance coverage (I)
	Age	+	Being aged 65 years or older (I)
	No vehicle access	+	Households without vehicles (HH)
	Internet access	+	Households without broadband internet access (HH)
Business level			
Categories	Variables	Sign	Description
Business diversity	Entropy index	–	It measures the diversity of industrial structures. The more diverse the industrial structure, the closer it gets to ln(20: number of industrial sectors). (See Equation 1)
	Herfindahl index	+	It evaluates the monopoly power of the industrial structure, and the more monotonous the industrial structure is, the closer it gets to 1. (See Equation 2)
Business scale	Scale of business (employment)	–	Employment/establishments
	Scale of business (payroll)	–	Annual payroll/establishments
Public (local aggregated) level			
Categories	Variables	Sign	Description
Economic capacity	GDP/population	–	Gross domestic product per capita
	Local government Expenditure/GDP	–	All amounts of money paid out by a government during its fiscal year per dollar of county GDP
	Net migration/ population	–	Measuring 10-year net migration by county per capita

(*Continued*)

https://doi.org/10.1017/age.2025.17

Table 2. (*Continued*)

Public (local aggregated) level			
Categories	Variables	Sign	Description
Social capital	Social capital index	–	Family Unity Subindex, Community Health Subindex, Institutional Health Subindex, and Collective Efficacy Subindex

Note: Data source from the US Census Bureau, Department of Commerce.
[1]By adjusting component cardinality (positive [+] or negative [–]), we ensure that positive component loading increases vulnerability, whereas negative component loading decreases vulnerability.
[2](HH) stands for households and (I) stands for individuals.
[3]Individual and household data are obtained using data from the ACS and the Census Bureau's Population Estimates Program (PEP), and the components are divided into binary indicators, with a maximum of 10.

income-to-poverty ratio, congestion at the per-room level, communication barriers, presence or absence of a person employed full-time, presence of disability, and health insurance coverage. Based on this, vulnerability at the household level is measured by calculating the proportion of households in the county that are flagged for three or more of the specified vulnerability variables.

Second, CRE is more accurate and timely than existing measures of social vulnerability and community resilience. CRE provides reliable measures of social vulnerability and community resilience for planning and deploying community resources. Also, CRE improves estimates of community resilience using small-scale regional modeling techniques (Willyard et al., 2022). Additionally, because it uses microdata, CRE can provide estimates and confidence needed to statistically determine whether there is a significant difference between two areas or time points (Willyard et al., 2022). In this context, CRE has data comprehensiveness that can be applied throughout the United States, and in terms of reliability and accuracy of estimates, CRE was cited as the household-level vulnerability in this study. Finally, CRE is an official program of the US Census Bureau and is committed to regular updates based on the annual releases of the ACS allowing for the CCVI to be updated alongside the update schedule of CRE.

Business level

Four indicators are included to determine the vulnerability of the industry at the county level: entropy index, Herfindahl–Hirschman index (HHI), number of employees per establishment, and annual payroll per establishment. In order to assess the vulnerability of the industrial aspects of individual counties, the study incorporates the entropy index and the HHI to measure diversity, along with two additional indicators that evaluate the scale of the industrial structure. Detailed explanations of these methodologies are provided below.

First, to measure vulnerability at the business level of a region, this study addresses the diversity of the industrial structure. Frenken et al. (2007) show that increasing unrelated variety (a concept related to increasing industry diversification in portfolio theory) is negatively associated with increased unemployment in the Netherlands. Watson and Deller (2017) also highlight that the industrial diversity of the county itself and its neighbors reduces unemployment rates during the post-Great Recession period. In a recent study, Chen et al. (2024) evaluated the 1-, 3-, and 5-year resilience of metropolitan statistical areas after the Great Recession and found that industry diversity supports

https://doi.org/10.1017/age.2025.17

increased resilience in these areas. Based on the link between increased industry diversity and reduced vulnerability, which has been highlighted and proven in many empirical studies, this study measures diversity in the following way:

Entropy index

Interest in diversity in regional science arose from severe fluctuations in employment and income, such as the Great Depression of the 1930s, and today, the concept of diversity is considered a fundamental element of regional economic development (Dissart, 2003). If the concept of diversity is combined with the local economy and industry, it suggests that diversity in the community's industrial structure can secure the economic stability of the region. In fact, the relationship between diversity and regional economic stability has been explained in empirical studies (Malizia and Ke, 1993; Wagner and Deller, 1993), suggesting that economic diversity can contribute to economic stability. Furthermore, economic diversity has been proven to be related to employment and income growth (Wagner and Deller, 1993).

As following empirical research from previous studies, this study assumes that the diversity of a specific region's industrial structure contributes to the stability of the regional economy and makes it more resilient to risks and uncertainties caused by external shocks. In general, the entropy index can be used as an appropriate indicator to replace other indicators related to diversity or competitiveness (Amroabady et al., 2017). However, Siegel et al. (1995) state that the concept of diversity includes a dynamic concept, and caution should be taken using a static concept of diversity index when proving the relationship between diversity and growth such as employment and income growth (Siegel et al., 1995). Additionally, descriptive regression analysis, which includes multiple benchmark indices, makes it difficult for the concept of diversity to include changes in economic structure (Siegel et al., 1995).

However, rather than capturing the impact of diversity on economic growth, this study focuses on resilience from risks such as external shocks (i.e., captures the static diversity of a region in a specific year). In addition, rather than using multiple benchmarks in regression analysis, potential issues related to correlation are complemented through PCA that considers the covariance between indicators. A detailed description of the PCA analysis is provided in the next section. In this study, the diversity of the county industrial structure is measured using the Shannon entropy index. Accordingly, we set that the higher the entropy index of the county, the lower the uncertainty caused by external shocks. Based on the number of industrial groups and the employee share of each industrial group[6] in each county, the formula for the entropy index is based on 20 two-digit North American Industrial Classification Systems (NAICS) sectors.[7] The higher the value of the entropy index (EI), the more diverse and less vulnerable the region is, as shown (equation 1) below.

[6]Each county's employees in each industry were sourced from 2020 US Census Bureau County Business Patterns data.

[7]The NAICS is the official classification system used by the North American federal statistical agency to classify businesses. The two-digit classifications are as follows: Agriculture, Forestry, Fishing and Hunting (11); Mining, Quarrying, and Oil and Gas Extraction (21); Utilities (22); Construction (23); Manufacturing (31–33); Wholesale Trade (42); Retail Trade (44–45); Transportation and Warehousing (48–49); Information (51); Finance and Insurance (52); Real Estate and Rental and Leasing (53); Professional, Scientific, and Technical Services (54); Management of Companies and Enterprises (55); Administrative and Support and Waste Management and Remediation Services (56); Educational Services (61); Health Care and Social Assistance (62); Arts, Entertainment, and Recreation (71); Accommodation and Food Services (72); Other Services (81); and Public Administration (92).

https://doi.org/10.1017/age.2025.17

$$EI = -\sum_{i=1}^{N} X_i \ln X_i \tag{1}$$

X = share of employment, i = economic sector

Herfindahl–Hirschman index

The use of indices as summary measures of diversity is particularly attractive because of their ability to synthesize vast amounts of information into a single value, easily interpreted number. The HHI, which comes from economics to measure market concentration and capture the degree of power or monopoly of a particular business sector, can be a useful tool for measuring diversity (Boydstun et al., 2014). Boydstun et al. (2014) argue that it is desirable to use a modified HHI when the number of industry groups is different for each comparison group. However, since the number of industry groups in each county is set to 20 in this analysis, the basic HHI is used. Assuming that regional stability becomes vulnerable in the event of external shocks when employment is concentrated in a specific industry, HHI index is calculated for each county using equation (equation 2) below. According to equation 2, the HHI value is equal to the square of the share of each industry category and the sum of these values. If the regional industrial composition lacks diversity and employment is structured around a specific industry, the HHI measure shows higher industrial vulnerability than other regions (close to 1). Likewise, regions with low HHI have high economic diversity (close to 0).

$$HHI = \sum_{i=1}^{N} (\bar{X}_i)^2 \tag{2}$$

$$\bar{X} = \frac{Number\ of\ employees\ in\ industry\ i}{Total\ Number\ of\ Employees}$$

Scale of business

As another indicator at the business level, we assume that business size is related to the stability of the county's business sector. Literature and statistical evidence indicate that larger-scale businesses promote job security and business stability (Ferguson, 1960). Storey (1994) highlights that small businesses are much more likely to cease trading than larger enterprises after a recession. Alesch et al. (2001) highlight that small businesses are less likely to reopen after a natural hazard. The choice to adopt firm size is based on the conceptual framework from a comprehensive literature review of community vulnerability to environmental disasters laid out by Zhang et al. (2009). In their framework, they highlight four forms of business vulnerability: capital, labor, supplier, and customer. In particular, the authors highlight smaller business sizes as a factor in increased capital vulnerability.[8] The number of employees per establishment and the annual payroll per establishment in each county are calculated and serve as proxies for business size. The cardinal direction was adjusted for the two indicators that measure business scale because the larger the average size of the business in a region, the less vulnerable it is. The number of employees, establishment, and annual payroll were calculated using data from the Census Business Builder.

[8] An anonymous reviewer pointed out that average firm size and business diversity may be antagonistic factors in the index for rural areas. While we agree this may be the case for some rural communities that are dominated by a large export-based industry, this does not preclude rural areas having a smaller number of larger businesses that are spread more equally across a larger number of economic sectors.

https://doi.org/10.1017/age.2025.17

Public level

At the public level, we expand two "place-based" concepts that go beyond individual or household aggregate data, such as the size of the economy produced relative to the community's population, net population inflow, financing capacity at the local government level, and social capital. Consequently, each county's economic capacity and the amount of local government expenditure are assumed to be closely related to the county's capacity to withstand external shocks. First, we include GDP per capita. Several studies have demonstrated the relationship between per capita GDP and vulnerability. For example, Cerra and Saxena (2008) showed that countries with higher GDP per capita in Asia, Africa, and Latin America were less susceptible to external shocks (e.g., currency crises, wars, etc.), suggesting that higher GDP per capita is associated with lower vulnerability. Similarly, Cellini and Torrisi (2009) found that Italian regions with the highest GDP per capita between 1890 and 2009 recovered most quickly from negative external shocks. Based on this, we use GDP per capita as a measure of vulnerability at the public level. We also use data on US local government expenditures from the Census Bureau (U.S. Census Bureau, 2021a). It was assumed that the higher the level of local government spending, the greater potential resources the community will have available to respond to external shocks (U.S. Census Bureau, 2020).

Next, this study focuses on the fact that the inflow migration into the community has a positive effect on the labor market and local finance of the community and can be attributed to income growth (Shumway and Otterstrom, 2015; Ozgen et al., 2010). In particular, Crown et al. (2018) and Biagi et al. (2018) showed that interregional migration increases are positively associated with resilience. Accordingly, it was assumed that the inflow of population had higher resilience to external shocks in the case of counties where the inflow migration continued based on the results of the study. To this end, net migration data for each county for 10 years from 2010 were obtained through the Applied Population Laboratory, the University of Wisconsin (Egan-Robertson et al., 2023).

This study assumes that the ability to maintain order between communities is closely related to resilience to various external shocks (Aldrich and Meyer, 2015). In particular, Aldrich and Meyer emphasize the important role of social capital and networks in disaster survival and recovery. Esther et al. (2022) also conducted a meta-synthesis of 187 studies, empirically demonstrating that structural and socio-cultural aspects of social capital are important factors in shock resilience outcomes. In this context, this study cited "The Geography of Social Capital in America," data specified that if the social capital index (SCI)[9] is high by region, the ability to maintain social order is high (United States Congress Joint Economic Committee, 2018). In this committee's research, social capital is explained as collective benefits derived from social relationships, networks, and cooperative activities between communities and individuals. In particular, it is described that social capital includes elements such as trust, shared values, mutual generosity, and cooperative behaviors such as working together or participating in formal groups. In a similar context,

[9]The county-level SCI consists of Family Unity Subindex, Community Health Subindex, Institutional Health Subindex, and Collective Efficacy. The details of the sub-index are as follows.

Family Unity Subindex: (1) share of births in the past year to women who were unmarried, (2) share of women ages 35–44 who are currently married (and not separated), and (3) share of own children living in a single-parent family. Community Health Subindex: (1) registered nonreligious nonprofits per 1,000, (2) religious congregations per 1,000, and (3) Informal Civil Society Subindex. Institutional Health Subindex: (1) average (over 2012 and 2016) of votes in the presidential election per citizen age 18+, (2) mail-back response rates for 2010 census, and (3) confidence in Institutions Subindex. Collective Efficacy: (1) Violent crimes per 100,000.

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social capital can be considered productive when it contributes to social cohesion and community well-being by fostering supportive relationships and enhancing collective effectiveness Furthermore, the research conducted by the committee then discusses how various forms of associated living, including family and community, can enhance or degrade social capital depending on the quality and scope of these social relationships and activities. This study follows the conceptual expansion of social capital and the index constructed by the United States Congress Joint Economic Committee (2018).

Method

In Section 3, we provide details on the data used at the household level, business level, and public (local aggregated) level. In this section, we calculate CCVI and specify the results using PCA to derive a single scalar measure for each level.

PCA is a method of compressing related sets and has the great advantage of being able to transform variables into a single scalar measure through dimensionality reduction (Abdi and Williams, 2010). PCA is one of the recommended approaches in grouping sub-indicators in the creation of a composite indicator (Nardo et al. 2005). The goals of the PCA analysis required in this study are as follows. Considering the distribution of the aforementioned variables, it extracts the most essential information from the variables and keeps only this important information to compress the size of the data set.

A seminal study in rural development using PCA is Deller et al. (2001). They use PCA to reduce 29 variables into five broad indicators of convenience and quality of life. Following a similar approach, we compress 18 individual variables into three broad levels of regional economic structure and then construct the CCVI. Tables 3 and 4 are the PCA[10] analysis results at the business level and the public (local aggregated) level. Through PCA analysis, each principal component is summed to derive the final CCVI result as shown in Equation three. When calculating the final index, we follow the research methods and SoVI approach of the University of South Carolina's Hazards Vulnerability & Resilience Institute (HVRI, 2016). **Comprehensive Community Vulnerability Index**[11] $= PC_{Private} + PC_{Business} + PC_{Public}$ (eq3)

The final principal component measure shows that most of the variables selected in this study play an important role. As a result of the cumulative variance of all four variables at the business level explained by PCA, the business level is the most effective at accounting for 51.4% of the variation. Similarly, at the public level, all four variables are important, but their explanatory power is only 31%.

Empirical results

In the previous section, we quantified the principal component values at the private (household) level, business level, and public level through PCA analysis and calculated the CCVI. The geographical distribution of vulnerability index values at the private (household) level, business level, and public level based on the principal components is presented in Figures 1–3, and the distribution of the CCVI is presented in Figure 4.

[10]The program R was used for PCA analysis, and the command princomp() was used to derive the principal components based on the covariance matrix.

[11]In the case of $PC_{Private}$, since the data related with private level that has already been scored by US Census Bureau CRE, the existing scores were used without principal component analysis. Also, the values of $PC_{Private}$, $PC_{Business}$, **and** PC_{Public} are the principal component values of each of the three levels, and in this study, the main component is expressed as a percentage score considering the cumulative distribution.

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Table 3. Summary of principal component analysis on business level

Principal component	Variables	Loading	Cumulative variance explained
$PC_{Business}$	Entropy index	0.596	51.39%
	Herfindahl index	0.536	
	Scale of business (Employment)	0.409	
	Scale of business (payroll)	0.435	

Table 4. Summary of principal component analysis on public (local aggregated) level

Principal component	Variables	Loading	Cumulative variance explained
PC_{Public}	GDP per capita	0.454	31.01%
	Local government Expenditure/GDP	0.453	
	Net migration per capita	0.521	
	Social capital index	0.563	

Vulnerability results are categorized based on percentile ranks: values over 0.8 are classified as "High," between 0.6 and 0.8 as "Intermediate High," between 0.4 and 0.6 as "Intermediate," between 0.2 and 0.4 as "Intermediate Low," and 0.2 or below as "Low." This system quantifies the degree of vulnerability from lowest to highest.

First, the 10 variables in the household-level categories are largely dependent on income. For example, variables such as education level, housing type, and lack of transportation are closely correlated to household income. Accordingly, when observing the geographical distribution of vulnerability at the household level, many counties in areas with high official poverty rates[12] are measured to have high vulnerability. Considering the geographical distribution of vulnerability assessed by socioeconomic factors at the private level (Figure 1), the number of counties in the high vulnerability group is 92 in Texas, 55 in Mississippi, 44 in Georgia, 37 in Arkansas, 37 in Kentucky, and 29 in Louisiana. Approximately 67.07% of counties in Mississippi, 49.33% in Arkansas, 48.48% in New Mexico, 45.31% in Louisiana, 43.28% in Alabama, and 36.96% in South Carolina show high vulnerability.

At the business level, which examines vulnerability in terms of the county's industrial structure and size, counties with relatively less diversity or scale of industrial structure are calculated to be more vulnerable (Figure 2). Recall that this study establishes that the smaller the industry and the lower the industrial diversity of the county, the more vulnerable the county is to external shocks such as natural disasters. In the business-level category, the geographical distribution of high vulnerability largely matches the Great Plains region of the United States. Industrial activity in the Great Plains primarily focuses on the extraction, handling, partial processing, and export of a few key products. In particular, the Great Plains primarily produces agricultural raw materials, which tend to be

[12]Official poverty rates refer to the proportion of the population whose pre-tax income is below three times the minimum food cost in 1963 (adjusted for inflation) (Shrider and Creamer, 2023).

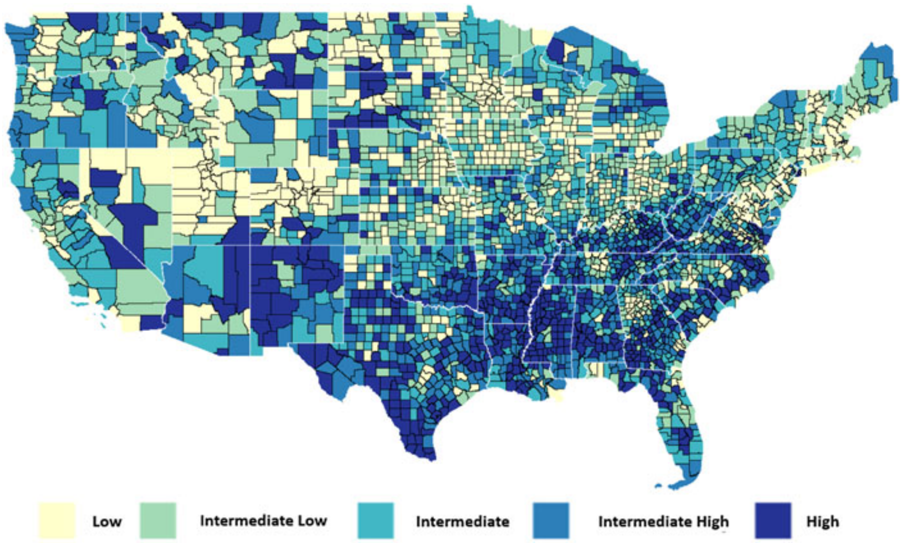

Figure 1. Vulnerability at private (household) level.

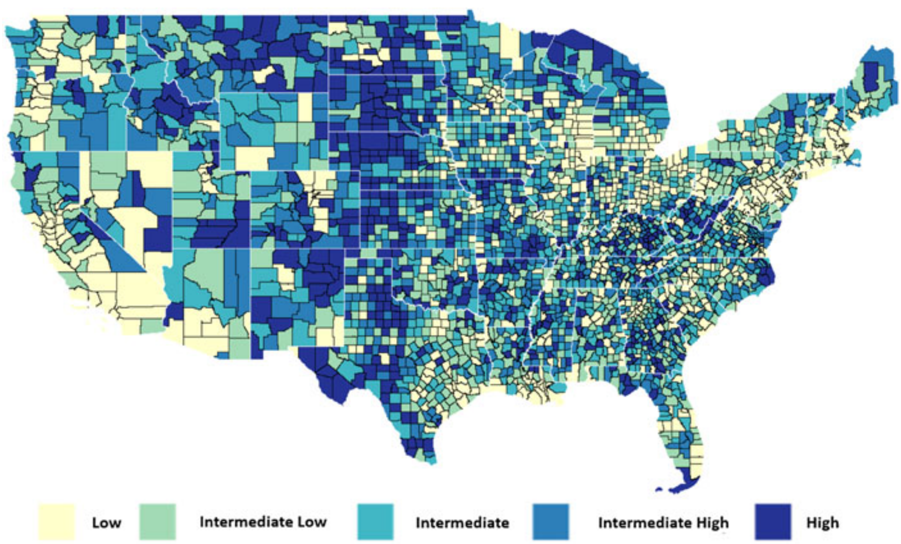

Figure 2. Vulnerability at business level.

transferred to industries outside the region in a raw or semi-processed state. Specifically, the states with a relatively high level of high business vulnerability include North Dakota (50.94%), South Dakota (48.48%), Nebraska (44.09%), and Montana (42.86%) of counties show high vulnerability.

Finally, the vulnerability of the county was quantified at the public level. Considering that collective benefits derived from social relationships within the community can

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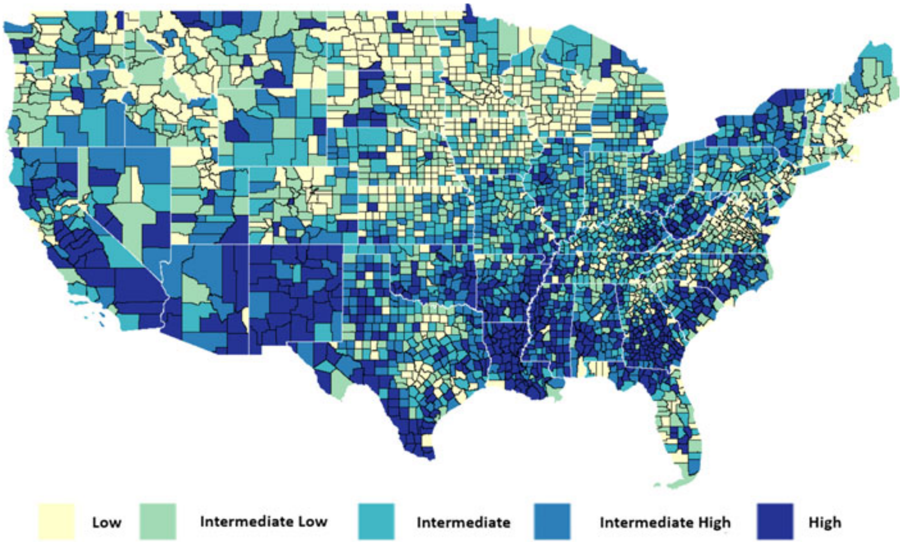

Figure 3. Vulnerability at public level.

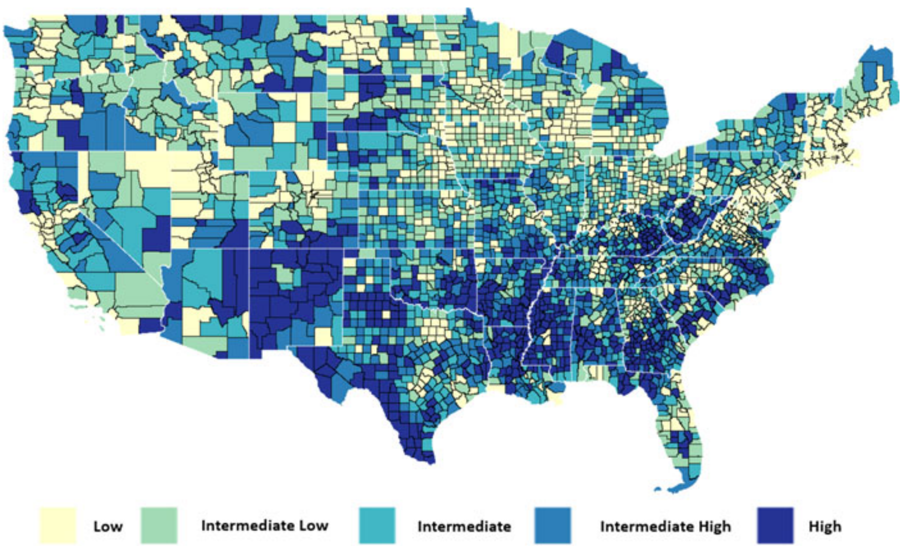

Figure 4. Comprehensive community vulnerability index.

contribute to maintaining order in the community, the SCI was included at the public level, and the overall regional resilience was considered by identifying the scale of county government expenditure and GDP. The geographical distribution of vulnerability assessed at the public level is shown in Figure 3. States with relatively high levels of vulnerability

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included New Mexico (75.76%), Louisiana (71.88%), Mississippi (60.98%), and Arizona (53.33%).

The geographical distribution of regional vulnerability calculated by comprehensively considering the three perspectives of private, business, and public is shown in Figure 4. It is calculated that the proportion of counties with high vulnerability is high in seven states, including most of the southern part of the United States. In New Mexico, Mississippi, Alaska, Arkansas, Louisiana, Oklahoma, and West Virginia, more than 40% of counties are classified as high vulnerability, and in Georgia, South Carolina, Alabama, Arizona, Texas, and Kentucky, more than 30% of counties are in high vulnerability.

To understand some of the spatial relationships in the data, spatial autocorrelation is analyzed, and cluster analysis results are presented. We follow Moran's (1948) methodology for testing spatial autocorrelation and present global Moran's I statistics for each county's CCVI. The global Moran's I statistic value is 0.4965, indicating positive spatial autocorrelation. This means that counties with similar levels of vulnerability are more likely to be located close together. The Moran' I statistic standard deviation (z-score) is calculated as 46.925, which indicates how many standard deviations the observed Moran's I is from the expected value under the null hypothesis. A sufficiently large z-score indicates that the observed spatial pattern is very unlikely to be the result of random chance. The corresponding p-value is less than 0.0001, indicating statistically significant spatial autocorrelation, indicating that the observed spatial autocorrelation (measured by Moran's I) is highly significant.

We use the local Moran's I test to decompose the global statistics into regional clusters and identify spatial trends in terms of high and low values (Figure 5). For example, areas classified as "HH" (High-High) indicate that both the county and its adjacent areas have higher vulnerability levels relative to the entire data set. Conversely, the "high" area in Figure 4 may have high values but may be surrounded by areas of variable values. To understand why certain regions in Figure 4 are classified as hotspots ("HH") but not necessarily "high," it is because Moran's I is a measure of spatial autocorrelation. We not only consider the value of the area itself but also consider how that value is related to surrounding spatial information (multi-polygon boundary information). A "Low" region in Figure 4 can actually become an "LH" in Figure 5 if it is surrounded by regions with higher values.[13] A "Low" area in one figure might appear as "LH" in another if it is bordered by regions of higher vulnerability, illustrating how local contexts can significantly influence overall vulnerability assessments.

Next, this study compares the newly constructed CCVI with the existing indices, CRE, SVI, and SoVI, and discusses the patterns and ways in which rural (nonmetro) and urban (metro) areas are classified as vulnerable. The classification of metro and nonmetro is based on the Rural-Urban Continuum Codes of the USDA Economic Research Service (ERS)[14] (Table 5). The CCVI places considerable emphasis on rural vulnerability, with 544

[13]In this study, the R programming language was used to calculate the Local Moran's I values for each county, employing the localmoran() function. Based on these calculations, counties were classified into four types of clusters: HH (High-High), where both the county and its neighboring counties have high values, indicating a regional concentration of high values; LL (Low-Low), where both the county and its neighbors have low values, showing a regional concentration of low values; HL (High-Low), where the county has high values but its neighbors have low values; and LH (Low-High), where the county has low values but its neighbors have high values. The clustering thresholds were set at 0.8 for high and 0.2 for low.

[14]The Rural-Urban Continuum Codes assign one of these nine codes to each US County and its census-designated equivalents (including remote areas). This study uses a method that raises the threshold population from 2,500 to 5,000 for the urban-rural distinction. It can be expanded to include county-level data by more detailed increased geographic granularity of metropolitan and nonmetropolitan subgroups.

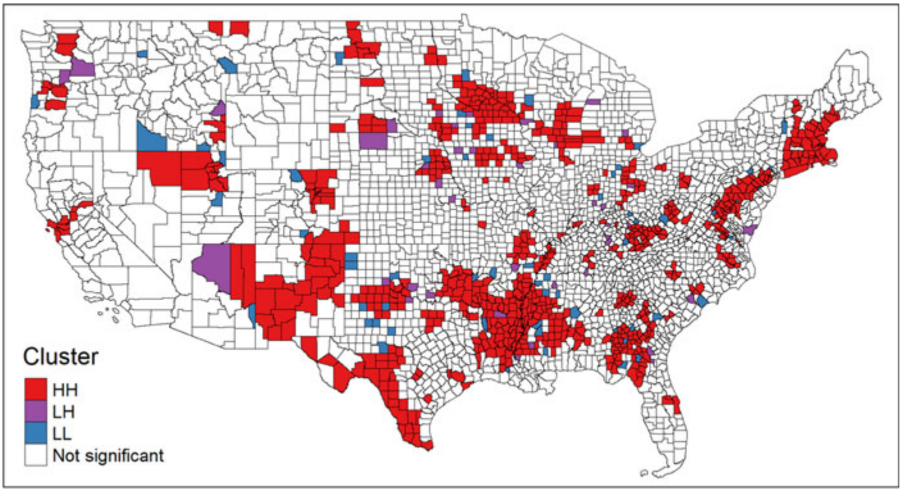

Figure 5. Spatial cluster analysis of comprehensive community vulnerability.

Table 5. Vulnerability indices by categories and metro-nonmetro classification

Index	Categories	Metro (A)	%	Nonmetro (B)	%	# Counties
CCVI	High	85	7.21	544	27.70	629
	Intermediate High	142	12.04	486	24.75	628
	Intermediate	202	17.13	427	21.74	629
	Intermediate Low	292	24.77	336	17.11	628
	Low	458	38.85	171	8.71	629
CRE	High	86	7.29	541	27.55	627
	Intermediate High	159	13.49	468	23.83	627
	Intermediate	234	19.85	397	20.21	631
	Intermediate Low	299	25.36	330	16.80	629
	Low	401	34.01	228	11.61	629
SVI	High	195	16.54	434	22.10	629
	Intermediate High	239	20.27	389	19.81	628
	Intermediate	239	20.27	390	19.86	629
	Intermediate Low	256	21.71	372	18.94	628
	Low	250	21.20	379	19.30	629
SoVI	High	47	3.99	582	29.66	629
	Intermediate High	114	9.67	518	26.40	632
	Intermediate	192	16.28	436	22.22	628
	Intermediate Low	300	25.45	326	16.62	626
	Low	526	44.61	100	5.10	626

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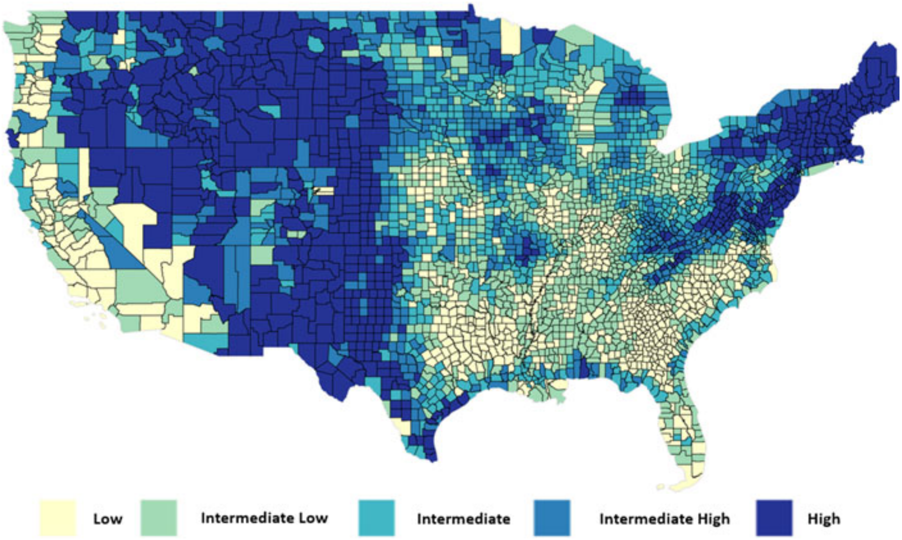

Figure 6. Extreme climate event score.

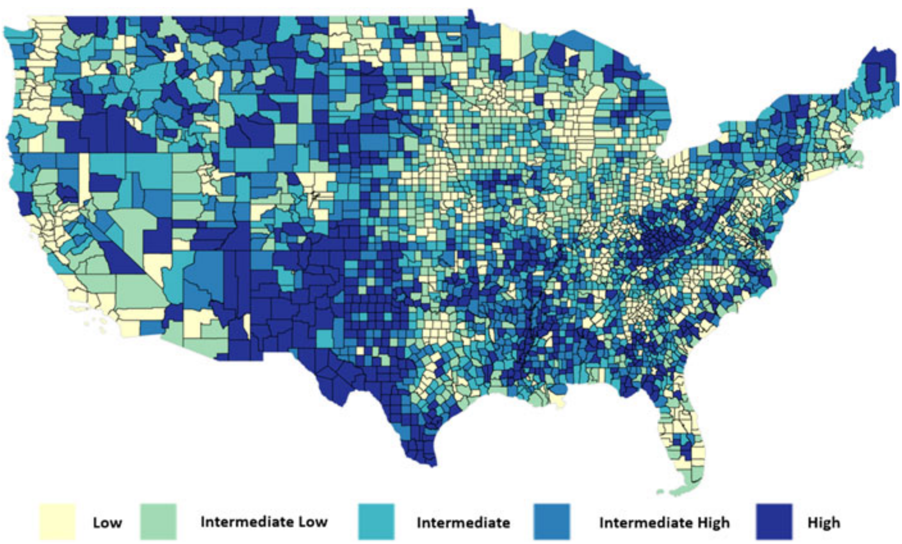

Figure 7. Climate-enhanced comprehensive community vulnerability index.

nonmetro counties classified as "highly vulnerable" compared to 85 metro counties. This means that only 7.2% of metro counties are highly vulnerable, compared to 27.7% of nonmetro counties. Along similar lines, urban areas dominate the "low vulnerability" category, with 458 counties classified as low vulnerable compared to only 171 rural counties (38.8% of metro counties classified as low vulnerable). This suggests that urban areas generally benefit from better inclusive resilience. This pattern highlights the systematic disadvantages

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Table 6. Cross-tabulation analysis of CCVI and CE-CCVI categories (unit: county)

CE-CCVI CCVI	Low	Intermediate low	Intermediate	Intermediate high	High
Low	462	166	4	0	0
intermediate low	145	274	194	15	0
Intermediate	22	160	236	208	3
Intermediate high	0	28	186	250	164
High	0	0	9	155	462

rural areas face in key dimensions such as regional economic stability and illustrates why public policies and support are important in rural areas. The CRE index follows a similar pattern to the CCVI, while the SVI shows a slightly more balanced distribution than the CCVI. For example, 434 rural counties are highly vulnerable, while only 195 are metropolitan counties. This suggests that the vulnerability classification results may vary depending on the measurement criteria of a particular index and emphasizes the CCVI's ability to more clearly reveal rural vulnerability.

This research ultimately focuses on the extensibility of the CCVI developed in this study. The flexibility of the CCVI through comprehensive conceptual expansion provides the possibility of further expansion by incorporating external variables such as extreme climate events, economic disruption, or policy changes. In this analysis, we present an extended version that considers climate conditions by incorporating extreme climate events into the CCVI framework (we distinguish CCVI and climate-enhanced CCVI (CE-CCVI)). For data on extreme weather events, we directly apply the extreme event values constructed by the US Climate Vulnerability Index from EDF, Texas A&M, and Darkhorse Analytics as the fourth vulnerability level in this study (Environmental Defense Fund, Texas A&M, and Darkhorse Analytics, n.d) (see Figure 6).[15] That is, the CE-CCVI adds extreme events to the CCVI and uses them as a fourth level of measurement within the vulnerability index, as illustrated in Figure 7. First, the correlation between the CCVI and CE-CCVI is 0.90, and it indicates a strong positive relationship. In the categorical classification, counties are distinguished as shown in Table 6. It shows consistency in the classification. 208 counties moved from "Intermediate" in the CCVI to "Intermediate High" in the CE-CCVI, reflecting the impact of extreme events. Similarly, 15 counties moved from "Intermediate Low" in the CE-CCVI to "Intermediate High" in the CCVI. This shift highlights the additional vulnerability captured by incorporating extreme weather events into the index. Looking at the state level, we can see how each state's vulnerability classification changes when climate is included. The states that increase in vulnerability when climate is taken into account (i.e., the CE-CCVI ha more counties classified as "High" than the CCVI) are Texas, where 40.16% (102 counties) are classified as High in the climate-inclusive index, compared to 32.68% (83 counties) in the baseline index. Montana also sees 41.07% (23 counties) classified as High in the extreme weather component, an increase of 11 counties compared to the baseline index. As demonstrated here, including events such as droughts, floods, and hurricanes can make the index more sensitive to climate-related risks. These attempts demonstrate the adaptability of

[15]This study directly cited Extreme events, a subitem of the US Climate Vulnerability Index constructed by EDF, Texas A&M, and Darkhorse Analytics, as a climate change risk. Extreme events integrate six factors – temperature-related, flood, storm, rainfall, drought, and wildfire – and provide a risk score for each county.

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a CCVI that incorporates external variables such as extreme climate events. The strong correlation between CE-CCVI and CCVI highlights shared ground, while the observed classification shifts suggest the potential for an expanded framework.

Validation tests of CCVI

The CCVI attempts to measure the vulnerability of communities to a variety of external shocks. It integrates data from multiple sectors, such as socioeconomic stability and the stability of the business and public sectors, to provide a holistic view of the strengths and weaknesses of communities. This section discusses the stepwise validation process of the constructed CCVI.

First, we verify that the CCVI is not an index that is isolated from existing indices through correlation analysis with existing vulnerability indices (see Table 7). Although the CCVI incorporates additional aspects that may not be covered by the CRE, such as economic diversity, it does not run counter to the trend of existing constructed vulnerability indices. It also shows correlations with the SVI and SoVI (0.5033 and 0.7070, respectively), suggesting that the CCVI not only assesses social vulnerability but also integrates it with other data to provide a more robust and nuanced understanding of what makes a community vulnerable or resilient. CCVI is mostly highly correlated with CRE, which was expected given that CRE represents a third of the CCVI index. Going back and taking a closer look at Figures 1 and 3, it can be seen that there is a similar spatial pattern of the public component of CCVI and CRE. At one level, this is not unexpected. If many of the public indicators are connected to the outcomes from the private indicators that make up CRE, it would be expected that these may be similar.

In the continuum of correlation analysis between vulnerability indices, the frequency distribution by category of CCVI category and CRE, SVI, RISK, and SoVI indices is presented in the crosstab results. Tables 8–10 show the category distribution of other indices based on the CCVI category, which shows how counties are actually classified between CCVI and each index. In the case of CRE, the CCVI High category was classified as CRE High the most (456 cases), and in the CCVI Low category, 422 cases were classified as CRE Low, showing a similar pattern in categorical classification to other indices.

Despite the aforementioned high correlation between CCVI and CRE indices statistically, the cross-tabulation results suggest there is still measurable variation between categories. For example, 181 (over 28%) of CCVI counties classified in the "Low" category were classified in "Intermediate Low by CRE." This is similar to the 148 (over 23%) "Low" CRE counties that are "Intermediate Low" in CCVI. The variation between the two indices is mostly differences between their two lowest and two highest categories. For example, only three countries that were "Low" in CCVI were either "Intermediate High" or "High" in CRE. Only 17 counties in "Low" CRE were in "Intermediate High" or "High" in CCVI.

In comparison with SVI, the highest matching value was observed between CCVI "High" and SVI "High" with 323 cases. However, when analyzing by categorical classification, it can be confirmed that the other categories are relatively evenly distributed. In the agreement with SoVI, 356 matches were observed between CCVI "High" and SoVI "High," and 406 matches were observed between CCVI "Low" and SoVI "Low."

Next, this study tests the validity of CCVI through structural equation modeling (SEM). We set up a latent variable as vulnerability and evaluated its impact on the outcome variables of population, place of work employment, and per capita income.[16] Vulnerability was

[16]The choice of testing against these common demographic and economic indicators are consistent with the step eight in the approach on constructing composite indicators outlined by the OECD (Nardo et al., 2005).

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Table 7. Correlation analysis of vulnerability indices

	CCVI	CRE	SVI	SoVI
CCVI	1.0000	–	–	–
CRE	0.8556	1.0000	–	–
SVI	0.5033	0.5807	1.0000	–
SoVI	0.7070	0.6621	0.4575	1.0000

Table 8. Cross-tabulation analysis of CCVI and CRE categories (unit: county)

CRE CCVI	Low	Intermediate low	Intermediate	Intermediate high	High
Low	422	181	23	3	0
Intermediate Low	148	271	178	27	4
Intermediate	42	133	275	157	22
Intermediate High	17	36	130	300	145
High	0	8	25	140	456

Table 9. Cross-tabulation analysis of CCVI and SVI categories (unit: county)

SVI CCVI	Low	Intermediate low	Intermediate	Intermediate high	High
Low	224	205	108	84	8
Intermediate Low	190	130	135	121	52
Intermediate	123	151	147	112	96
Intermediate High	71	96	146	165	150
High	21	46	93	146	323

Table 10. Cross-tabulation analysis of CCVI and SoVI categories (unit: county)

SoVI CCVI	Low	Intermediate low	Intermediate	Intermediate high	High
Low	406	142	53	20	8
Intermediate low	145	205	160	89	29
Intermediate	45	169	177	153	85
Intermediate high	23	85	153	215	151
High	7	25	85	155	356

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Table 11. Model fit statistics

Model	χ^2	Q	CFI	TLI	SRMR	RMSEA
SEM	342.157	31.11	0.959	0.922	0.035	0.098

Note: The result indicates a good fit if CFI > 0.95, TLI > 0.90, SRMR < 0.05, and RMSEA < 0.08.

Table 12. Standardized factor loadings and variance explained

Measurement	Standardized factor loadings	Variance explained (%)	Residual variance (%)	p-value
CCVI	0.930***	86.6	13.4	<0.001
CRE	0.918***	84.3	15.7	<0.001
SVI	0.585***	34.2	65.8	<0.001
SoVI	0.746***	55.7	44.3	<0.001

Note: * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 13. Effects of vulnerability on outcome variables

Outcome variable	Estimate (unstandardized)	Std. error	*z*-value	p-value	Standardized coefficient (std. all)
Population	−310.222***	29.359	−10.566	<0.001	−0.192
Employment	−173.818***	33.079	−5.255	<0.001	−0.097
Income (per capita)	−421.951***	45.368	−9.301	<0.001	−0.170

Note: * p < 0.05, ** p < 0.01, *** p < 0.001.

measured by four observed variables: CCVI, CRE, SVI, and SoVI. In particular, CCVI was found to be the core indicator that most strongly explains Vulnerability with a standardized factor loading value of 0.930. This suggests that CCVI plays the most important role in evaluating vulnerability. As a result of the analysis, the model demonstrated excellent fit with a Comparative Fit Index (CFI) of 0.959, a Tucker–Lewis Index (TLI) of 0.922, and a standardized root mean square residual (SRMR) of 0.035. However, the root mean square error of approximation (RMSEA) was somewhat high at 0.098. This indicates that the model may not fully capture the complexity of some aspects of the data. Therefore, future studies might consider further improvements to the model, as detailed in Table 11. When examining the indirect effect based on CCVI, CCVI showed a negative impact on the outcome variable through vulnerability. The indirect effect on the outcome variable population was the largest at −0.179, while income had an indirect effect of −0.158, showing a medium level of influence. The indirect effect on employment was relatively small at −0.090, but still significant (see Tables 12–14).[17] This shows that vulnerability, including CCVI, has an

[17]The method for calculating the indirect effect of CCVI on the outcome variable follows the method of Bollen (1989), which states that the relationship between variables is calculated by dividing it into Direct Path and Indirect Path during SEM analysis.

Indirect Effect = Factor Loading of CCVI × Direct Effect of Vulnerability on Outcome.

1. Indirect Effect for P = 0.930 × −0.192 = −0.17856 (−0.179), 2. Indirect Effect for E = 0.930 × −0.097 = −0.09021 (−0.090), 3. Indirect Effect for I = 0.930 × −0.170 = −0.1581 (−0.158)

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Table 14. Decomposition of effects on outcome variables

Outcome variable	Direct effect (standardized)	Indirect effect	Total effect (standardized)	p-value	Significance
Population	−0.192	−0.179	−0.371	<0.001	***
Employment	−0.097	−0.09	−0.187	<0.001	***
Income (per capita)	−0.17	−0.158	−0.328	<0.001	***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

overall negative impact on policy, economic, and social outcomes. In the analysis of variance, CCVI showed 13.4% of residual variance, explaining 86.6% of the variability of vulnerability, confirming that it was the most reliable indicator of those tested in Table 12.

Summary and conclusions

This study quantified the relative vulnerability of 3,141 counties. We constructed a CCVI that takes into account the household level, business level, and public level. A total of 18 variables related to household socioeconomic characteristics, business size and diversity, local government economic size, social capital, and net migration were used. In the case of existing vulnerability indices, the index was constructed by using the socioeconomic characteristics of individuals and the household units. This study attempted to expand the concept of vulnerability indices by "place-based" measures by considering the business structure within the community and the potential ability to maintain the existing stability of the private. However, since this study used a factor summation method that simply sums the principal components ($PC_{Private}$, $PC_{Business}$, and PC_{Public}) values of HVRI's SoVI recipe, the respective weights for household, business, and public vulnerability were not taken into account. The CCVI constructed in this study can be used as preliminary data for officials and emergency response planners to identify and map communities that may be most in need of support before, during, and after an exogenous shock. Additionally, by providing the relative vulnerability of the community at each level (household level, business level, and public level), it is possible to provide evidence on which areas are more vulnerable than others and triage steps taken to mitigate vulnerability. In other words, a community interested in vulnerability can assess its relative vulnerability areas compared to other communities. We would like to finally emphasize that comprehensive community vulnerability can influence key economic decisions of individuals, including those related to migration decisions. As long as variables that can affect local residents' migration decisions are included in the CCVI, this can serve as a sufficient basis for local residents' migration.

In addition, this study evaluates the possibility of extending the CCVI and shows that the vulnerability index can be deepened by including exogenous variables such as climate change. In particular, the CE-CCVI extended in this study reflects the role that climate change can have in an existing vulnerability index, incorporating extreme climate events such as temperature rise, drought, wildfire, increased precipitation, flood, and storm. It is expected that more detailed and precise measurements of community vulnerability will be possible through an extended attempt to reflect exogenous variables in addition to climate. In addition, the results of this study suggest that if additional variables reflecting the characteristics and differences of vulnerability between urban and rural areas can be reflected in the CCVI in future studies, the accuracy of the index can be improved.

https://doi.org/10.1017/age.2025.17

Data availability statement. The data used in this study are available upon request from the corresponding author.

Funding statement. This work is supported by the Hatch project award no. CT0508, LAB# 94590, from the US Department of Agriculture's National Institute of Food and Agriculture.

Competing interests. The authors declare no competing interests.

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Appendix

Table A1. Components of social vulnerability (SV) in CRE

Community resilience estimates (CRE)		
Categories	Variables	Type
Social vulnerability (SV)	SV 1: Income-to-poverty ratio (IPR) < 130 percent	HH
	SV 2: Single or zero caregiver household – only one or no individuals aged 18–64	HH
	SV 3: Unit-level crowding with > 0.75 persons per room	HH
	SV 4: Communication barrier defined as either limited English-speaking households or no one with a high school diploma	HH
	SV 5: No one in the household is employed full-time, year-round (not applied if all residents are aged 65+)	HH
	SV 6: Disability posing constraint to significant life activity (hearing, vision, cognitive, ambulatory, self-care, independent living difficulty)	I
	SV 7: No health insurance coverage	I
	SV 8: Being aged 65 years or older	I
	SV 9: No vehicle access	HH
	SV 10: Households without broadband internet access	HH

Note: Households (HH) and individuals (I).

Table A2. Descriptive statistics of variables

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Entropy index	0.00	2.07	2.24	2.18	2.37	2.70
HHI index	0.07	0.12	0.14	0.16	0.17	1.00
Scale of business (employment)	1.71	8.90	11.64	12.01	14.73	49.49
Scale of business (payroll)	45.88	360.26	503.65	565.17	690.99	4078.38
GDP per capita (dollar)	6,094	25,989	34,759	39,875	46,578	934,766
Local government expenditure/ GDP	0.00	0.11	0.14	0.16	0.19	1.47
Net migration per capita	−0.44	−0.04	0.00	0.00	0.05	0.52
Social capital index	−4.32	−0.61	0.00	0.00	0.63	2.97

https://doi.org/10.1017/age.2025.17

Table A3. Vulnerability correlation matrix across private, business, and public levels

	Private level (CRE)	Business level	Public level
Private level (CRE)	1		
Business level	0.3821	1	
Public level	0.5387	0.1867	1

Table A4. Vulnerability correlation matrix of business level

	Entropy index	HHI index	Scale of business (Employment)	Scale of business (Payroll)
Entropy index	1			
HHI index	0.9386	1		
Scale of business (Employment)	0.1276	−0.0145	1	
Scale of business (Payroll)	0.1741	0.0277	0.8377	1

Table A5. Vulnerability correlation matrix of public level

	GDP per capita	Local government expenditure/GDP	Net migration per capita	Social capital index
GDP per capita	1			
Local government Expenditure/GDP	0.1920	1		
Net migration per capita	0.0328	0.0371	1	
Social capital index	0.0686	0.0155	0.1970	1

Cite this article: Kim, E. and J. M. Fannin. 2025. "Creating the Comprehensive Community Vulnerability Index." *Agricultural and Resource Economics Review*. https://doi.org/10.1017/age.2025.17