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Reconceptualizing rurality: Exploring community capital to identify distinct rural classes in the United States

Jennifer L. Cruz[a], Douglas A. Luke[b,*], Rachel M. Ceballos[c], Shoba Ramanadhan[a], Karen M. Emmons[a]

[a] Harvard T.H. Chan School of Public Health, 677 Huntington Ave, Boston, MA, 02115, USA
[b] Brown School at Washington University in St Louis, 1 Brookings Drive, St. Louis, MO, 63130, USA
[c] University of Utah Health Huntsman Cancer Institute, 2000 Cir of Hope Dr, Salt Lake City, UT, 84112, USA

ABSTRACT

Background: In population health research, rurality is often defined using broad population density measures, which fail to capture the diverse and complex characteristics of rural areas. While researchers have developed more nuanced approaches to study neighborhood and area effects on health in urban settings, similar methods are rarely applied to rural environments. To address this gap, we aimed to explore dimensions of contextual heterogeneity across rural settings in the US.
Methods: We conducted an exploratory latent class analysis (LCA) to identify distinct classes of rurality. Using the Community Capitals Framework, we collated and analyzed nationally representative data for each domain of rural community capital across all rural census tracts in the US (n = 15,643). Data for this study were sourced from ten publicly available datasets spanning the years 2018–2021. To provide preliminary validation of our findings, we examined the Social Vulnerability Index (SVI) percentile rankings across the identified rural classes.
Results: A four-class model solution provided the best fit for our data. Our LCA results identified four distinct classes of rurality that vary in terms of capital types: Outlying (n = 3,566, 22.7%), Developed (n = 3,210, 20.5%), Well-Resourced (n = 4,896, 31.3%), and Adaptable (n = 3,981, 25.4%). The mean SVI percentile rankings differed significantly across these classes, with Well-Resourced having the lowest and Adaptable the highest mean percentile rankings.
Conclusions: We identified different types of rurality at the census tract level that fall along a social gradient as indicated by variation in SVI percentile rankings. These findings highlight that each rural class has a unique combination of community capitals. This nuanced approach to conceptualizing rurality provides the opportunity to identify interventions that meet specific rural communities' unique strengths and needs.

1. Introduction

1.1. Background

Persistent rural-urban health inequities in the US pervade various domains of population health, spanning critical areas such as cancer, cardiovascular disease, and maternal health (Cross et al., 2020; Kozhimannil et al., 2019; Lewis-Thames et al., 2022). The weight of such inequities is underscored by growing geographic disparities in mortality rates. Cross et al. (2021) estimated that from 1999 to 2019, rural populations consistently experienced higher all-cause age-adjusted mortality rates than urban populations, with the rural-urban inequity increasing threefold. When further disaggregating data by racial and ethnic identity, all-cause mortality rates of rural racially minoritized populations are consistently higher than their White counterparts (Probst et al., 2020).

The dynamic interplay of geographic location, sociodemographic characteristics, and structural determinants in rural settings are drivers of poor health and make some populations more vulnerable to disparate health outcomes. For instance, 85% of US counties experiencing persistent poverty are rural *and* have large racialized minority population concentrations (US Department of Agriculture, 2021). Entrenched structural racism actively shapes the multifaceted contexts people live in via residential segregation, discriminatory financial practices, and political disempowerment (Braveman et al., 2022; Swope et al., 2022). As a result, systemic factors deny rural racialized minority populations access to opportunities for upward economic mobility. Given poverty's association with health-risk behaviors (e.g., alcohol use, unhealthy diet, physical inactivity), rural and racial patterns of poverty are further echoed in disparate exposure to health risk factors (Cook et al., 2020; Hartley, 2004). Health inequities are further compounded by limited access to healthcare, resulting in delayed care and poorer prognoses (Nielsen et al., 2017).

Despite the ongoing development of programs and interventions to

* Corresponding author.
E-mail address: DLUKE@wustl.edu (D.A. Luke).

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address these determinants at the population level, their relevance and effectiveness in rural contexts remain unclear. As highlighted by Smith et al. (2016) in their analysis of the implementation of evidence-based health interventions (EBIs) in 70 rural communities across the US, the translation of EBIs to the rural context is challenging. Common barriers include cultural misalignment (e.g., language differences), practical limitations (e.g., time, funding), barriers to community partner engagement (e.g., inability to integrate new practices into underfunded), and limited capacity (e.g., healthcare workforce retention) (Smith et al., 2016). Recognizing the diversity within and across rural settings is essential for identifying context-specific health solutions. However, our understanding of rurality and its nuances in population health remains limited.

The operationalization of rurality in population health research typically reflects federal categorizations employed to distinguish urban from rural areas at a high level (Hall et al., 2006). However, such categorizations are relatively blunt, given their dependency on population density as a core measure (Table 1).

To overcome the limitations of these commonly used rural categorizations, the Health Resources and Services Administration (HRSA) brings these three overlapping definitions together to identify all rural areas comprehensively. They complement the U.S. Department of Agriculture's definition of rural to include representation of distance to services and population density. Their definition of rural consists of all non-metro counties, all metro census tracts with RUCA codes 4 to 10, large area metro census tracts of at least 400 square miles in area with a population density of 35 or less per square mile with RUCA codes 2 to 3, and all outlying metro counties without an urbanized area (Health Resources & Services Administration, 2022). By offering a more inclusive identification of rural areas across the US, HRSA's approach allows for the opportunity to conduct more accurate population health research among rural communities.

For over 30 years, population health researchers have studied the impact of neighborhood and area effects in urban settings to understand how context shapes health (Ribeiro, 2018). This body of work highlights the heterogeneity of urban areas regarding sociocultural features, access to social services, and built environments and how these factors are associated with health outcomes and inequitable disease distribution (Arcaya et al., 2016). It underscores the need to focus on neighborhood-level contextual factors that may increase residents' vulnerability to poor health. In contrast, little context-focused research has been conducted in rural areas (Richman et al., 2019), resulting in a limited understanding of the heterogeneity of rural communities.

Table 1
Examples of commonly used definitions of rural employed by federal institutions.

Defining Federal Institution	Measure(s)	Categorizations	Designation
US Census Bureau (2016)	Population density	Urbanized Areas (UAs): 50,000 or more people	Urban
		Urban Clusters (UCs): 2500 - 49,999 people	Urban
		Areas outside of UAs or UCs	Rural
Office of Management and Budget (2010)	Population density	Metro area: urban core of 50,000 or more people	Urban
		Micro area: urban core of 10,000–49,999 people	Rural
		Counties outside of Metro or Micro areas	Rural
U.S. Department of Agriculture (2023)	Population density	Metropolitan cores: Rural-Urban Community Area (RUCA) codes 1-3	Urban
	Urbanization	Micropolitan and small town cores: RUCA codes 5-9	Urban
	Daily commuting	Rural areas: RUCA code 10	Rural

1.2. *Taking a systems approach to understanding the rural context in public health*

Public health often relies on a reductionist single exposure-outcome approach to identify isolated contextual risk factors affecting population health. However, this method is "systems preserving," assuming the outcome distribution remains constant even when exposure and covariates are intervened on (Jackson & Arah, 2020). A systems approach, in contrast, captures the interactions of distinct environmental factors and their collective impact on health outcomes (Diez Roux, 2011). This approach helps identify underlying contextual mechanisms and critical intervention points. To fully understand the diverse and dynamic nature of rurality, it is essential to move beyond defining it by population density and adopt systems-aligned approaches that consider interconnected contextual dimensions.

The Community Capitals Framework (CCF, Fig. 1) exemplifies a systems approach to understanding the rural context. Explicitly developed for rural settings as an alternative assets-based tool for strategic planning and measurement, the CCF identifies seven domains of capital—natural, cultural, human, social, political, financial, and built. These domains operate independently and interactively to contribute to a rural community's overall function and sustainability (Flora, 2004). They comprehensively capture the resources available to rural communities, suggesting that all rural communities possess these seven types of capital at varying levels. The CCF's systems approach provides insights into how intervening on one type of capital impacts the others. Overemphasizing one capital can lead to community decapitalization, compromising economic security, social inclusion, ecosystem health, and overall well-being of rural communities (Flora et al., 2015).

The CCF holds significant promise in population health for understanding the rural context, yet its use remains limited. Unlike traditional definitions of rurality, which often overlook the complexities of rural communities, the CCF provides a more nuanced approach to identifying the drivers of rural health inequities. However, while the CCF offers valuable insights, it has mostly been used as a tool in the adaptation and evaluation of programs in rural settings rather than comprehensively examining the rural context itself (Moyers-Kinsella et al., 2024; Olfert et al., 2018).

What remains underexplored is the potential of the CCF as a foundational tool to analyze the broader social, economic, and environmental factors shaping health in rural areas before interventions are designed. Applying the CCF in this way could offer critical insights to

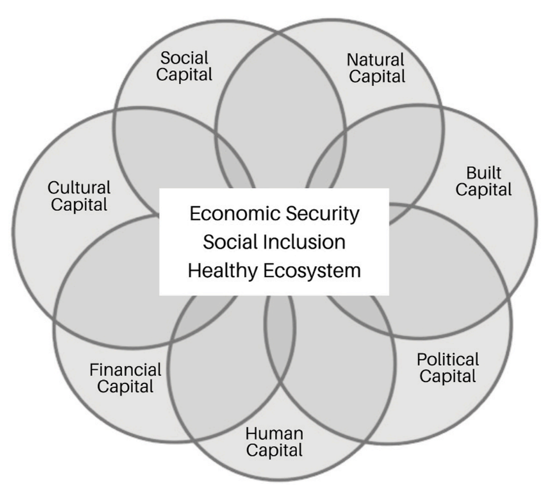

Fig. 1. Community capitals framework
adapted from Flora, C.B., 2004. Social aspects of small water Systems.Journal of contemporary water research & education 128, 6–12.

ensure that interventions are more contextually relevant and effective across rural populations.

1.3. Present study

This study explores the heterogeneity of rurality in the US by identifying distinct classes of rurality using the CCF as an organizing framework. We conducted a theory-driven, exploratory latent class analysis (LCA) with nationally representative data, considering measurable aspects of the CCF community capitals related to differential health outcomes of all US rural census tracts. With the final class model, we examined the variation of rural contextual characteristics to demonstrate qualitative differences across rural classes. Finally, we validated our final class model by assessing the variation in social vulnerability distribution across the identified rural classes, illustrating the relevance of our findings. To our knowledge, this is the first comprehensive attempt to reconceptualize and define rurality in population health literature; thus, this work is descriptive rather than hypothesis-driven.

2. Methods

2.1. Study population

The study population for this analysis includes all rural census tracts as defined by the HRSA, which offers the most inclusive definition by incorporating the USDA's RUCA codes to identify rural tracts within metro counties (Health Resources & Services Administration, 2022). HRSA provides a comprehensive list of designated rural counties and census tracts based on 2010 Census Bureau geographies, which are the geographies we will carry forward for this analysis. Given HRSA's role in funding rural health initiatives, using their definition ensures the relevance of our findings to public health practice. This approach results in a final study population of 15,643 census tracts across all 50 states.

2.2. Measures

2.2.1. Community capitals

The CCF guided the selection of variables for our LCA model. We included census tract-level measures of community characteristics representative of each of the seven community capitals to ensure we captured the many facets of the rural context. All measures were from publicly available data sources. The data for this analysis, from 2018 to 2021, were mapped to the 2010 Census Bureau geographies in alignment with the HRSA rural designations, as previously described. Appendix Table A further describes indicator items, measures, and sources.

Political Capital: Political capital involves the distribution of resources by those in power, the capacity of communities to influence policy decisions, and their participation in policy implementation. Two indicators were used to capture political capital: linking social capital and Indigenous land. Linking capital refers to ties that facilitate resource flow between institutions (public or private) and the communities they serve (Berkman & Kawachi, 2014). The linking capital measure was drawn from Aldrich and Kyne (2022) Social Capital Index (SoCI) replication dataset. The SoCI is a measure that captures bonding, bridging, and linking social capital using 19 indicators derived from publicly available data for the United States (Kyne & Aldrich, 2020). In this index, linking capital indicators include political linkage, local government linkage, state government linkage, federal government linkage, and political activities (Kyne & Aldrich, 2020). Indigenous land was a binary variable indicating if any portion of a census tract overlapped with an American Indian/Alaska Native area or Hawaiian homeland. This indicator served as a proxy for sovereignty status (Hoss, 2019) or for Indigenous communities not federally recognized but with governing bodies making resource allocation decisions.

Social Capital: Social capital is the network of trusted relationships among individuals, organizations, and communities that enable society to function. We included bridging and bonding capital indicators to represent social capital, measured using the SoCI previously described (Kyne & Aldrich, 2020). Bridging capital is resources shared across networks with varying sociodemographic characteristics (Berkman & Kawachi, 2014). The SoCI bridging capital measure includes five indicators – religious organizations, civic organizations, charitable, fraternal, and union ties. Bonding capital refers to resources shared within networks with similar sociodemographic characteristics (Berkman & Kawachi, 2014). The SoCI bonding capital measure includes nine indicators: race similarity, ethnicity similarity, educational equality, race/income equality, employment equality, gender income similarity, language competency, communication capacity, and non-elder population (below 65 years of age). Distinguishing between bridging and bonding capital allows a more detailed understanding of social capital's positive or negative impact on health outcomes in a particular context (Berkman & Kawachi, 2014).

Human Capital: Human capital refers to the investments individuals make in their education, training for employment, and health that can be utilized to create economic value. Indicator items representing employment status (% of age 16+ population employed), educational attainment (% of age 25+ population with a high school diploma only), and health insurance coverage (% of population without health insurance) assessed human capital. We differentiated educational attainment in the rural context by using a measure of obtaining a high school diploma only. Educational attainment in population health research often defaults to completing a four-year bachelor's degree due to the evidenced relationship with improved health outcomes (Hout, 2012). However, this approach does not account for the contextual dependency of educational attainment, particularly in rural settings (Schmitt-Wilson & Downey, 2018). Contextual factors, such as employment opportunities, significantly shape educational attainment among rural populations. In these settings, people are more likely to be employed by low- and middle-skill jobs that do not require bachelor's degrees and are primarily skill-based (e.g., agricultural, manufacturing, and retail jobs) (Davis et al., 2023). Intentionally using the measure of high school diplomas in our analysis allows us to capture the educational and employment contexts in rural settings.

Natural Capital: Natural capital considers environmental elements of the rural context– weather, landscape, air, water, soil, and biodiversity. Three indicators captured aspects of natural capital that could be confined to and compared across census tracts. These included the annual mean concentration of particulate matter (PM 2.5 μg/m3), total unplanned land (acres), and total water area (acres).

Built Capital: The infrastructure that supports the function of society is considered built capital. We included six measures of built capital that capture past and present investments in built infrastructure: household plumbing (% of housing units lacking complete plumbing facilities), access to health clinics (distance in miles to nearest health clinic), walkability index, local work (number of jobs within 45-minutes), medically underserved designation, and public schools (total number of public, charter, and magnet schools).

Cultural Capital: Cultural capital encompasses the racial/ethnic makeup of a community, languages spoken, religions practiced, and customs. It emphasizes a community's cultural wealth, described by Yosso (2005) as "the array of cultural knowledge, skills, abilities, and contacts possessed by socially marginalized groups that often go unrecognized and unacknowledged." We specifically drew on familial and linguistic cultural capital domains. Familial capital refers to the cultural knowledge (community history, traditions, memories, intuition) shared among kin and the broader community (Yosso, 2005). Measures of racialized minority population (% of the population that are not white non-Hispanic), foreign born (% of population born outside of the US), average household size, intergenerational household (% of households that have children and non-caretaking grandparents), and elder population (% of Population 65+) represented this domain. Linguistic capital refers to the social and intellectual skills gained by communicating in multiple languages (Yosso, 2005). A measure of linguistically isolated households (% of limited English-speaking households) represented this domain.

Financial Capital: The availability of the monetary resources necessary to promote economic, social, and infrastructure development is considered financial capital. We included eight indicator items: median household income (dollars, inflation-adjusted to 2019), owner-occupied housing (% of owner-occupied households), poverty experience (% of population living below the poverty level), no vehicle (% of households with no vehicle available for use), public assistance use (% of households with public assistance income or food stamps/SNAP), internet access (% of households with any internet subscription), underserved banking area designation, and household crowding (% of households with >1 person per room).

We used the census tract-level measures to create binary variables, which is preferable for LCA due to their interpretability (Weller et al., 2020). Using county-level measures as thresholds, we dichotomized census tract-level variables as above (1) or below (0) county averages. We dichotomized indicator variables that represented designations (e.g., medically underserved areas) as either being designated (1) or not being designated (0).

2.2.2. Validation measure

The primary variable examined in our validation analysis was the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry (CDC/ATSDR) Social Vulnerability Index (SVI) (Flanagan et al., 2011). The SVI was selected because of its representativeness of the US, strong evidence of validity (face, content, and construct), and growing use in public health (Freelander et al., 2024; Mah et al., 2023).

The SVI comprises 16 social factor indicators grouped into four summary themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation (Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry, 2022). Each US census tract receives a summary score (themes and overall score) and then are put in rank order. Higher percentile rankings indicate greater social vulnerability.

2.3. Data analyses

First, we assessed the local independence assumption to select variables for the preliminary model (Sinha et al., 2021). The LCA model assumes conditional independence among indicator variables, with associations attributed to the latent class (Nylund-Gibson & Choi, 2018). We checked candidate variables for collinearity, and highly correlated variables ($r > 0.80$) were further evaluated for potential violations of the local independence assumption (Young, 2017). No violations were found.

Next, we fit fully saturated LCA models that included all 30 initial binary indicator variables, testing solutions with one to six classes. A full information maximum likelihood estimator with an expectation-maximization procedure was used to handle missing data (Lanza et al., 2007). Random starting values ($n = 100$) assessed model identification and convergence. To select the final LCA model, we evaluated information criteria (Log-Likelihood, G2, Akaike Information Criterion, Bayesian Information Criterion) and model stability, choosing the solution with the lowest statistics and highest stability for the best fit (Collins & Lanza, 2009; Nylund-Gibson & Choi, 2018).

After selecting the best class model, we reviewed the predicted probabilities of each indicator across classes to simplify the model. Indicators were removed if they did not meet any the following criteria: 1) had predicted probabilities below 0.2 across all classes, 2) showed limited variability in predicted probabilities, or 3) overlapped conceptually with other indicators. This approach ensured the model included only quantitative and qualitatively significant indicator items. Using this criterion, we omitted eight variables from our model moving forward: underserved banking area designation, Indigenous land, medically underserved areas, public schools, intergenerational households, elder population, household crowding, and total water.

After selecting the 22 final indicator items, we re-ran the models and assessed the fit statistics. We chose the best-fitting class model based on statistical fit and interpretability (Collins & Lanza, 2009). Predicted probabilities were used to assign each census tract to a class and identify qualitative differences. Negatively worded indicators were recoded to represent the likelihood that a census tract exceeds its county's measure. Labels were derived from the assets-based grounding of the CCF.

We assessed the relationship between rural class designations and the 2020 census tract-level SVI percentile rankings as a preliminary validation of the final class model, serving as proof of concept for the classification approach. We used generalized linear models to examine the variation in mean percentile rankings based on rural class designations and SVI rankings (themes and overall summary). Additionally, we visually explored the distribution of SVI percentile rankings across the identified rural classes.

We used R version 4.3.1 for processing, validation analyses, and visualizations (RStudio Team, 2023). To run the LCA models, we used SAS software version 9.4 (SAS Institute Inc., 2023) and the PROC LCA package (Lanza et al., 2007).

3. Results

3.1. Model selection

Table 2 presents the LCA results from the final 22 indicator item models ranging from one to six classes. Generally, the model with the lowest fit statistic values and high model convergence indicates a better fit for the data (Collins & Lanza, 2009). Considering these points, in addition to interpretability, we selected the four-class model to move forward and further examine the differences between classes.

3.2. Latent profiles of rural classes

The overall sample across the classes was well distributed, with 22.7%, 20.5%, 31.3%, and 25.4% of census tracts assigned to Classes 1–4, respectively. Predicted probabilities range from 0 to 1, with 0.5 being an even chance. We considered probabilities above 0.7 as "high" and below 0.3 as "low" to aid interpretation (see Appendix Table B for the predicted probabilities and Appendix Fig. A for a line plot). Classes with at least half of a capital's items in the high or low regions indicate those items are salient to their characterization and were the primary basis for each class label. Table 3 provides details of the composition of contextual characteristics across each class.

Class 1 (Outlying Rural): Census tracts in class 1 ($n = 3556$; 22.7%) had lower predicted probabilities of built capital than their respective county averages. This class was labeled "Outlying Rural" to reflect the distinct remoteness of its tracts. We found Outlying Rural tracts to have the highest mean proportion of: people having a high school diploma only (38%), people being uninsured (11.3%), total unplanned land (106,536 acres), households lacking full plumbing (6.8%), and average household size (2.58 people). Additionally, Outlying Rural tracts had the lowest mean proportion of employment (92.9%), average annual mean PM 2.5 (6.34 μg/m3), and household internet access (71%).

Class 2 (Developed Rural): Predicted probabilities for class 2 tracts ($n = 3210$; 20.5%) indicated higher built and financial capital but lower natural capital than their respective county averages. This class was labeled "Developed Rural" as they are tracts with infrastructure and resources that enhance the quality of life and economic well-being. We found that Developed Rural census tracts have the highest mean proportion of households with internet access (78%). They also had the lowest mean proportion of people with a high school diploma only (32%) and households lacking full plumbing (3.5%).

Table 2
Latent class analysis model fit statistics.

# of Classes	LL	DF	G^2	AIC	BIC	% Identified
	Model Fit Criteria					
1	−229007.1	4194281	165582.9	165626.9	165795.4	100
2	−210372.7	4194258	128314.0	128404.0	128748.6	100
3	−206272.7	4194235	120114.0	120250.0	120770.7	66
4	**−203206.5**	**4194212**	**113981.7**	**114163.7**	**114860.6**	**100**
5	−201220.3	4194189	110009.2	110237.2	111110.2	69
6	−200303.2	4194166	108175.1	108449.1	109498.2	33

Abbreviations: LL- Log-Likelihood, DF- Degrees of Freedom, AIC- Akaike Information Criterion, BIC- Bayesian Information Criterion.

Table 3
Composition of contextual characteristics across the identified latent classes (mean and standard deviation).

	Rural Class				
	Overall	**Class 1**	**Class 2**	**Class 3**	**Class 4**
		Outlying	Developed	Well-Resourced	Adaptable
Characteristic					
Size (%)	**15,643**	**3556 (22.7)**	**3210 (20.5)**	**4896 (31.3)**	**3981 (25.4)**
Linking capital	0.60 (0.10)	0.60 (0.10)	0.61 (0.09)	0.61 (0.08)	0.58 (0.10)
Bridging capital	0.60 (0.13)	0.60 (0.13)	0.60 (0.13)	0.61 (0.13)	0.58 (0.12)
Bonding capital	0.58 (0.07)	0.58 (0.07)	0.57 (0.07)	0.60 (0.06)	0.56 (0.07)
% High school-educated population	36 (9)	38 (8)	32 (9)	36 (9)	36 (8)
% Uninsured population	9.5 (6.3)	11.3 (6.8)	8.3 (6.0)	8.0 (5.4)	10.7 (6.5)
% Employed population	94.2 (4.3)	92.9 (5.7)	95.3 (3.3)	95.5 (2.9)	93.0 (4.5)
Annual mean PM2.5 (μg/m3)	6.42 (1.24)	6.25 (1.23)	6.34 (1.26)	6.38 (1.22)	6.69 (1.23)
Total unplanned land (acres)	79,545 (198,905)	106,536 (253,734)	82,526 (219,239)	104,044 (181,091)	22,907 (119,562)
% Households lacking full plumbing	4.7 (5.5)	6.8 (7.5)	3.5 (4.5)	4.6 (4.6)	4.0 (4.7)
Distance to clinic (miles)	5.7 (8.3)	7.1 (9.9)	4.9 (11.1)	7.2 (5.7)	3.5 (6.1)
Walkability index	6.04 (2.53)	4.71 (1.94)	6.93 (2.14)	4.61 (1.52)	8.25 (2.41)
Jobs within 45 minutes	5372 (6296)	3524 (5137)	6050 (6640)	4402 (5546)	7668 (6998)
% Population racialized minority	22 (23)	25 (27)	21 (20)	14 (16)	30 (25)
% Population foreign-born	4.6 (6.0)	4.7 (7.1)	4.9 (5.7)	3.2 (3.9)	5.8 (6.9)
% Linguistically isolated households	1.71 (4.11)	2.22 (5.32)	1.45 (3.22)	0.81 (1.96)	2.59 (5.15)
Average household size	2.50 (0.35)	2.58 (0.42)	2.46 (0.35)	2.53 (0.29)	2.43 (0.35)
% Households with no vehicle	6.5 (5.8)	6.4 (5.9)	5.6 (4.9)	3.5 (2.8)	10.9 (6.6)
% Poverty experience	16 (10)	19 (9)	13 (7)	11 (6)	23 (11)
Median household income	51,205 (15,453)	46,580 (11,970)	55,629 (14,772)	59,974 (14,773)	40,808 (11,192)
% Owner-occupied housing	72 (15)	75 (11)	71 (13)	82 (8)	57 (14)
% Household public assistance use	15 (9)	17 (9)	12 (7)	10 (6)	21 (10)
% Household internet access	75 (11)	71 (11)	78 (9)	78 (9)	72 (10)

Class 3 (Well-Resourced Rural): The largest proportion of census tracts (n = 4896; 31.3%) were class 3. Tracts in this class had predicted probabilities that indicated that their financial capital was higher than their respective county averages, whereas built and cultural capital was lower. We labeled this class “Well-Resourced Rural” to reflect its possession of capital indicative of assets necessary for stability and development in such tracts. The distinguishing features of Well-Resourced Rural census tracts were their highest average proportion of the population employed (95.5%), mean distance from health clinics (7.2 miles), median household income ($59,974), and proportion of owner-occupied households (82%). These tracts also had the lowest average: proportion of the population uninsured (8%), walkability index (4.61), proportion of the population being racialized minorities (14%), proportion of the population being foreign-born (3.2%), proportion of households with no vehicle (3.5%), proportion of population that experienced poverty (11%), and proportion of household public assistance use (10%).

Class 4 (Adaptable Rural): Class 4 census tracts (n = 3981; 25.4%) had higher predicted probabilities of built and cultural capital and lower predicted probabilities of social and financial capital than their respective county averages. This class was labeled “Adaptable Rural” to reflect the existing physical infrastructure and cultural resilience that help address local social and financial scarcities. Census tracts in this class had the highest average annual mean PM 2.5 (6.69 μg/m3), walkability index (8.25), jobs within 45 min (7,668), proportion of population being racialized minority (30%) and foreign-born (5.8%), linguistically isolated households (2.59%), households that lacked a vehicle (10.9%), proportion of experienced poverty (23%), and used public assistance (21%). Adaptable Rural census tracts also had the lowest averages of linking, bridging, and bonding capital (0.58, 0.58, 0.56, respectively), total unplanned land (22,907 acres), distance to health clinics (3.5 miles), median household income ($40,808), and proportion of owner-occupied households (57%).

The radar plots in Fig. 2 visually represent the predicted probabilities of the final indicator variables by class and demonstrate how each class has a distinct combination of community capitals. Interactive maps illustrating the spatial distribution of the rural classes across the US are available at: cruzjl.github.io/rural_class_map/.

3.3. Class validation

Our crude validation approach suggested that the four classes identified differed significantly across each SVI theme (i.e., socioeconomic status, household characteristics, racial and ethnic minority status, housing type and transportation) and the SVI overall (Appendix Table C). Well-resourced and developed rural tracts consistently had the lower mean SVI percentile rankings across SVI themes and overall, whereas outlying and adaptable rural tracts had the inverse.

Fig. 3 illustrates the differences in SVI percentile ranking distributions across rural classes. The final four-class model revealed meaningful

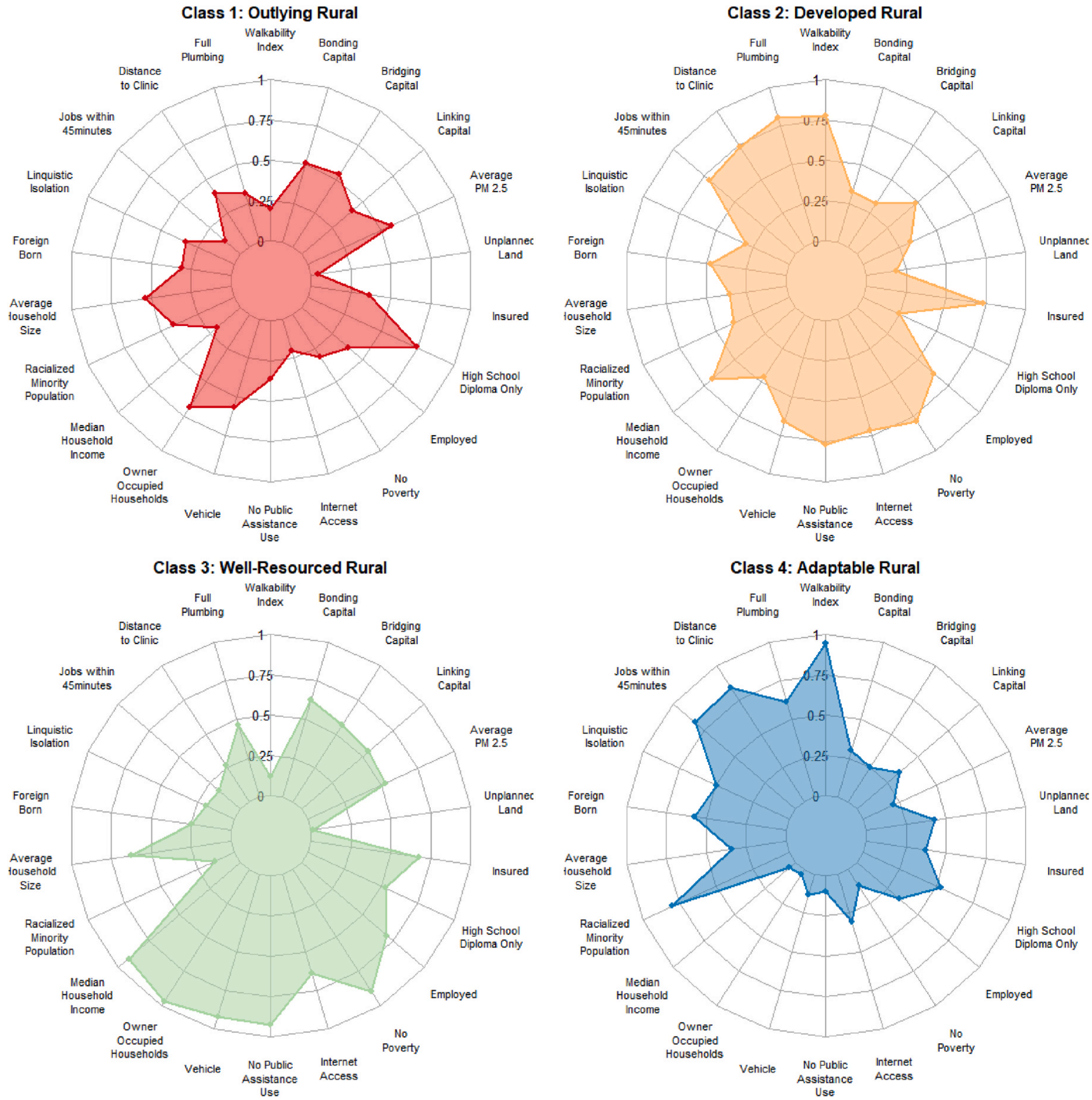

Fig. 2. Predicted probability of indicator items across the four identified latent classes.

variations in social vulnerability. Adaptable rural tracts show higher concentrations in higher SVI percentiles, indicating increased social vulnerability. Outlying rural tracts had similar distributions but less extreme concentrations in higher percentiles. Well-Resourced tracts generally had the lowest SVI percentile rankings. Developed rural tracts display the most variability across SVI themes, with a nearly symmetrical SVI percentile ranking distribution overall.

4. Discussion

Our study explored rural heterogeneity in the US using a latent class analysis to identify distinct classes of rural census tracts. We found that a four-class solution was the best fit and demonstrated discrete patterns of rural contextual characteristics based on the Community Capitals Framework. Statistically significant differences between classes in mean SVI percentile rankings further evidenced the contextual heterogeneity across the US.

The four classes showed distinct variations in core community capitals that may contribute to overall well-being, as indicated by SVI scores. For example, Well-Resourced Rural tracts (31.3% of tracts) were high in financial and natural capital but low in built and cultural capital and were found to be the least socially vulnerable. Conversely, Adaptable Rural tracts (25.4% of tracts) were high in built and cultural capital but low in social and financial capital and were found to be the most socially vulnerable. These findings suggest that our classes capture distinct differences in community capitals, reinforcing relationships between community capitals, and how their interactions may shape community outcomes, including health.

These results contribute to a growing body of research on neighborhood typologies and variation in population health outcomes in the US (Humphrey et al., 2019; Roth et al., 2023; Shariff-Marco et al., 2021). By narrowing our focus on rural areas, we extend findings from recent work that identified two profiles that captured a majority of the rural census tracts in the US with distinct differences in racial and ethnic makeup (Zewdie et al., 2024). We show that there are more than two types of rural contexts in the US and that rural settings were most heterogeneous across built, cultural, and financial capital characteristics. These characteristics are reflected in well-documented barriers rural populations face when accessing healthcare (e.g., limited access to services, experienced discrimination, and economic constraints) (Douthit

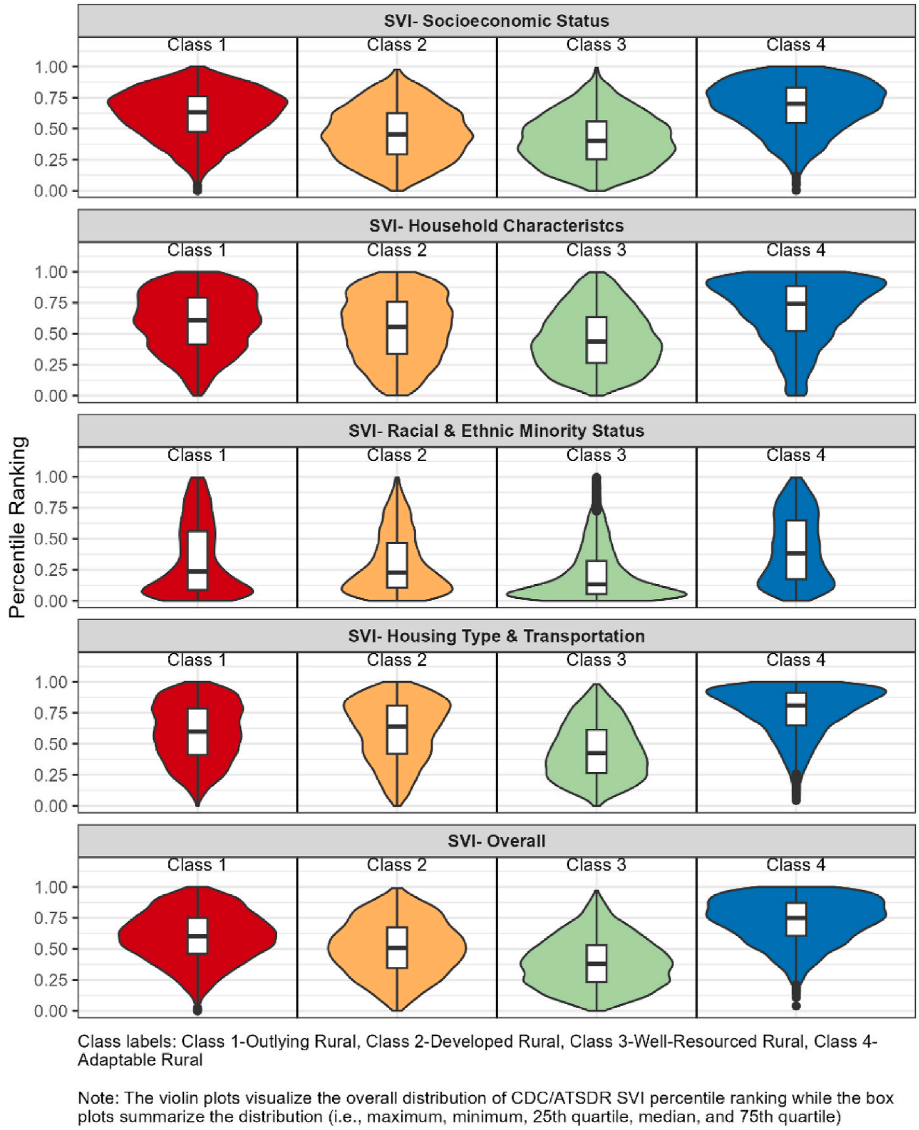

Fig. 3. Distribution of 2020 CDC/ATSDR Social Vulnerability Index percentile rankings by identified rural classes.

et al., 2015).

An important contribution of our results is that the commonly discussed rural contextual barriers may not be entirely generalizable across the US. Instead, each identified rural class has a unique combination of interconnected community capitals, highlighting their specific strengths and needs, often overlooked when identifying key intervention points to improve health. For example, Adaptable Rural areas may benefit most from policies raising the minimum wage, as increased income can improve health by enabling access to necessities like healthy food, housing, and healthcare, while they may benefit less from increasing access to healthcare infrastructure due to already high levels of built capital. Given the significant role of context in implementing policies and practices to eliminate health inequities, it is essential to consider all contextual aspects—including social, economic, and infrastructure factors—to avoid harmful unintended consequences (May et al., 2016). Neighborhood research emphasizes the need to deeply understand contextual characteristics, including population composition and the underlying system of a specific geographic area, to identify the most effective interventions to improve population health (Diez Roux & Mair, 2010). Our work extends this conceptualization to rural health by providing a baseline understanding of contextual differences as variations in underlying systems.

Additional findings from our study demonstrate the differential experience of social vulnerability by rural class, confirming the identified classes' utility to population health equity. Research has shown that higher area-level social vulnerability is associated with worse health outcomes such as COVID-19 (Dasgupta, 2020). Thus, our findings suggest that rural areas with higher SVI rankings face a greater risk of poorer health.

The present study found that Adaptable Rural tracts consistently had the highest mean SVI percentile rankings, housing large proportions of racialized minority and low-income populations. In contrast, Resourced Rural tracts, with majority white and high-income populations, had the lowest mean SVI percentile rankings. These results are well situated in a body of work documenting the impacts of ongoing racial discrimination on rural Indigenous, Black, and Latino communities, who constitute the majority of the 25% racialized minority population in rural areas (Kozhimannil & Henning-Smith et al., 2016; Stern, 2021). As proposed by Burton et al. (2013), the "new" rural America has become more racially and economically segregated due to the ongoing economic interdependence of metropolitan and rural areas. With patterns of decreased job stability, increased migration and immigration of low-income racially minoritized populations, and shaped concentrations of poverty, rural communities are increasingly experiencing detrimental racial health inequities (Burton et al., 2013).

Our results uniquely identify the assets of the most socially vulnerable rural areas, particularly built and cultural capital. By highlighting these assets, we aim to move beyond simply identifying health inequities and population vulnerabilities, instead focusing on leveraging community resources and strengths to inform targeted population health solutions that address inequities more effectively. Approaches like appreciative inquiry, which ground solutions in current community strengths and address weaknesses without focusing solely on deficits, align well with the CCF. Recognizing and leveraging these assets and strengths emphasizes that enhancing community resilience is crucial for achieving health equity.

4.1. *Strengths and limitations*

A key strength of this work is our innovative use of the CCF to explore rural heterogeneity, highlighting the value of interdisciplinary approaches in population health research. This approach fosters innovative thinking and supports an asset-based framing that is less common in population health literature. Additionally, our use of the SVI enhances our findings' applicability by identifying social vulnerabilities and various related health risks across different rural classes, allowing for more targeted public health interventions tailored to the unique needs of each community.

Using census tracts as our analytic unit limited the analysis by restricting the choice of indicator items, potentially introducing spatial bias by not fully capturing social and structural processes in rural geographies. Some community capitals, like social and political capital, are not easily measured, and the proxy measures we employed may not fully reflect these constructs. However, linking diverse, publicly accessible data sources enabled us to capture aspects of all seven capitals outlined by the CCF, offering a baseline comprehensive view of rural community assets.

While latent class analysis helped identify meaningful rural typologies at baseline, simplifying measures into binary indicators may have limited the full diversity of classification. Future research should address spatial biases, refine measurements of community capitals, and explore alternative methods such as latent profile analysis or machine learning approaches to enhance the classification of rurality. Despite these limitations, our findings provide a solid foundation for future research in this area.

5. Conclusion

The objective of our study was to enhance the understanding of rurality in the US by identifying distinct patterns of rural contextual characteristics using the CCF. Our findings highlight two key points: first, rural settings exhibit significant contextual heterogeneity, as shown by our identification of four diverse classes of rurality; second, social vulnerability and related health outcomes vary by rural class, as evidenced by differences in SVI percentile rankings. Given that population health research often treats rurality as a monolith, these findings underscore the need for a holistic approach to understanding the rural context. Future research should investigate how this variation in rurality influences specific health outcomes that are known to inequitably burden rural populations, such as cancer, cardiovascular disease, or maternal health. Such research will offer further validation of the identified rural classes. Practice-based efforts should focus on developing policies that acknowledge rural diversity and ensure that interventions are adapted to the unique characteristics of each rural class.

CRediT authorship contribution statement

Jennifer L. Cruz: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Douglas A. Luke:** Writing – review & editing, Supervision, Methodology. **Rachel M. Ceballos:** Writing – review & editing, Supervision. **Shoba Ramanadhan:** Writing – review & editing, Supervision. **Karen M. Emmons:** Writing – review & editing, Supervision.

Ethical statement

The authors confirms that all described research procedures were performed in compliance with the ethical principles, laws, and guidelines enforced by the Harvard Longwood Campus Institutional Review Board at Harvard University. The present study (Protocol # IRB23-0237) was determined as non-human subjects research by the Harvard Longwood Campus Institutional Review Board on 2/22/2023.

Financial disclosure statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

Appendix Table A
Indicator variables for latent class analysis model

Capital	Indicator Item	Census Tract Measure	County Measure	Year	Source	Citation
Political	Linking capital	Linking social capital index[a]	Median linking social capital index[a]	2019	HDV[i]	Aldrich and Kyne (2022); Fraser et al. (2022)
	Indigenous land	American Indian/Alaska Native areas/ Hawaiian homeland indicator[b]	N/A	2019	USCEN	US Census Bureau (2021)
Social	Bonding capital	Bonding social capital index[c]	Median bonding social capital index[c]	2019	HDV[i]	Aldrich and Kyne (2022); Fraser et al. (2022)

(*continued on next page*)

Appendix Table A (*continued*)

Capital	Indicator Item	Census Tract Measure	County Measure	Year	Source	Citation
	Bridging capital	Bridging social capital index[d]	Median bridging social capital index[d]	2019	HDV[i]	Aldrich and Kyne (2022); Fraser et al. (2022)
Human	Employed population	Percentage of civilian labor force that is employed (ages 16+)	"	2019	ACS	US Census Bureau (2020) [j]
	High school-educated population	Percentage of Population with only high school diploma (ages 25+)	"	2019	ACS	US Census Bureau (2020) [j]
	Uninsured population	Percentage of Population with no health insurance coverage	"	2019	ACS	US Census Bureau (2020) [j]
Natural	Particulate Matter (PM2.5) concentration	Annual mean of Particulate Matter (PM2.5) concentration (μg/m3)	"	2019	WUSTL-ACAG	van Donkelaar et al. (2021)
	Total unplanned land	Total land area (acres) that is not protected from development[e]	Median land area (acres) that is not protected from development across county census tracts[f]	2018	EPA	US Environmental Protection Agency (2023)
	Total water	Total water area (acres)[e]	Median water area (acres) across county census tracts[f]	2018	EPA	US Environmental Protection Agency (2023)
Built	Households lacking complete plumbing	Percentage of housing units lacking complete plumbing facilities	"	2019	ACS	US Census Bureau (2020) [j]
	Distance to clinic	Distance in miles to the nearest health clinic, calculated using population-weighted tract centroids	Median distance in miles to the nearest health clinic, calculated using population-weighted tract centroids	2019	AHRQ	Agency for Healthcare Research and Quality (2022)
	Walkability index	Walkability index[g]	Median walkability index across county census tracts [h]	2021	EPA	US Environmental Protection Agency (2023)
	Work within 45-minutes	Jobs within 45 min auto travel time, time-decay weighted[g]	Median jobs within 45 min auto travel time, time-decay weighted across county census tracts [h]	2021	EPA	US Environmental Protection Agency (2023)
	Medically underserved	Medically underserved designation	N/A	2021	HRSA	Health Resources & Services Administration (2022)
	Public schools	Total public schools (traditional public, charter & magnet) in tract[k]	N/A	2018	NaNDA	Kim et al. (2021)
Cultural	Racialized minority population	Percentage population of color (not White Non-Hispanic)	"	2019	PHDGCP	Testa et al. (2022) [l]
	Linguistically isolated households	Percentage of limited English-speaking households	"	2019	ACS	US Census Bureau (2020) [j]
	Foreign-born population	Percentage of Population that is foreign-born	"	2019	ACS	US Census Bureau (2020) [j]
	Average household size	Average household size	"	2019	ACS	US Census Bureau (2020) [j]
	Intergenerational household	Percentage of children living with grandparent householder whose grandparent is not responsible for them	"	2019	ACS	US Census Bureau (2020) [j]
	Elder population	Percentage of population ages 65 and over	"	2019	ACS	US Census Bureau (2020) [j]
Financial	Median household income	Median household income (dollars, inflation-adjusted to 2019)	"	2019	ACS	US Census Bureau (2020) [j]
	Owner-occupied housing	Percentage of occupied housing units: owner-occupied	"	2019	ACS	US Census Bureau (2020) [j]
	Poverty experience	Percentage of persons below poverty	"	2019	PHDGCP	Testa et al. (2022) [l]
	No vehicle	Percentage of housing units with no vehicle available	"	2019	ACS	US Census Bureau (2020) [j]
	Household public assistance use	Percentage of households with public assistance income or food stamps/SNAP	"	2019	ACS	US Census Bureau (2020) [j]
	Household internet access	Percentage of households with any internet subscription	"	2019	ACS	US Census Bureau (2020) [j]
	Underserved banking area	Underserved banking area designation	N/A	2021	OCC	Office of the Comptroller of the Currency (2021)
	Household crowding	Percentage crowding (>1 person per room)	"	2019	PHDGCP	Testa et al. (2022) [l]

Notes.

[a] Linking social capital index indicator items (5): political linkage (% of total voting age population who are eligible for voting), local government linkage (% of total local government employees working for local governments), state government linkage (% of total state employees working for the state governments), federal government linkage (% of total federal employees working for the federal agencies), political linkage-political activities (attended political rally/speech/organized protest- % of total).

[b] Spatial intersection operation is conducted to determine if County/ZCTA/Tract boundaries cross any AIAN boundaries. 1 indicates an intersection and 0 means that they don't intersect.

[c] Bonding social capital index indicator items (9): race similarity (0 complete homogeneity = to 1 complete heterogeneity), ethnicity similarity 0 complete = homogeneity to 1 complete heterogeneity), educational equality (negative absolute difference between % of total population with college education and % of total population with less than high school education), race/income equality (Gini coefficient (0 perfect equality to 1 perfect inequality), employment equality (absolute difference between % of total employed and % of total unemployed labor force), gender income similarity (gender income fractionalization (0 complete = homogeneity to 1 complete heterogeneity), language competency (% of total population proficient English speaker), communication capacity (% of total households with a telephone), and non-elder population (% of total population below 65 years of age).

[d] Bridging social capital index indicator items (5): Religious organizations (religious organizations per 10,000 persons), civic organizations (civic organizations per 10,000 person), social embeddedness-charitable ties (member of charitable organization- % of total), social embeddedness-fraternal ties (member of fraternal order- % of total), and social embeddedness-union ties (member of union- % of total).

[e] Census tract level estimates were calculated by summing all census block groups within a single tract.

[f] County level estimates were calculated by taking the median of all census tracts within a single county.

[g] Census tract level estimates were calculated by taking the average of census block groups within a single tract.
[h] County level estimates were calculated by taking the median of all census tracts within a single county.
[i] Census tract level measures created and provided by (Fraser et al., 2022), County level measurements provided by (Aldrich & Kyne, 2022).
[j] American Community Survey data were accessed via the tidycensus package in R using a Census Bureau Data API (Walker & Herman, 2024).
[k] Census tracts were dichotomized based on school count with 1+ public schools being coded as 1 and 0 public schools being coded as 0.
[l] Variables from the Public Health Disparities Geocoding Project (Testa et al., 2022) were sourced from the American Community Survey. American Community Survey data were accessed via the tidycensus package in R using a Census Bureau Data API (Walker & Herman, 2024).

Source abbreviations: Washington University St. Louis Atmospheric Composition Analysis Group (WUSTL-ACAG), US Environmental Protection Agency (EPA), Public Health Disparities Geocoding Project (PHDGCP), American Community Survey (ACS), Harvard Datatverse (HDV), Office of the Comptroller of the Currency (OCC), Agency for Healthcare Research and Quality (AHRQ), Health Resources and Services Administration (HRSA), National Neighborhood Data Archive (NaNDA), US Census (USCEN)

Appendix Table B
Probability of community characteristics across identified latent classes

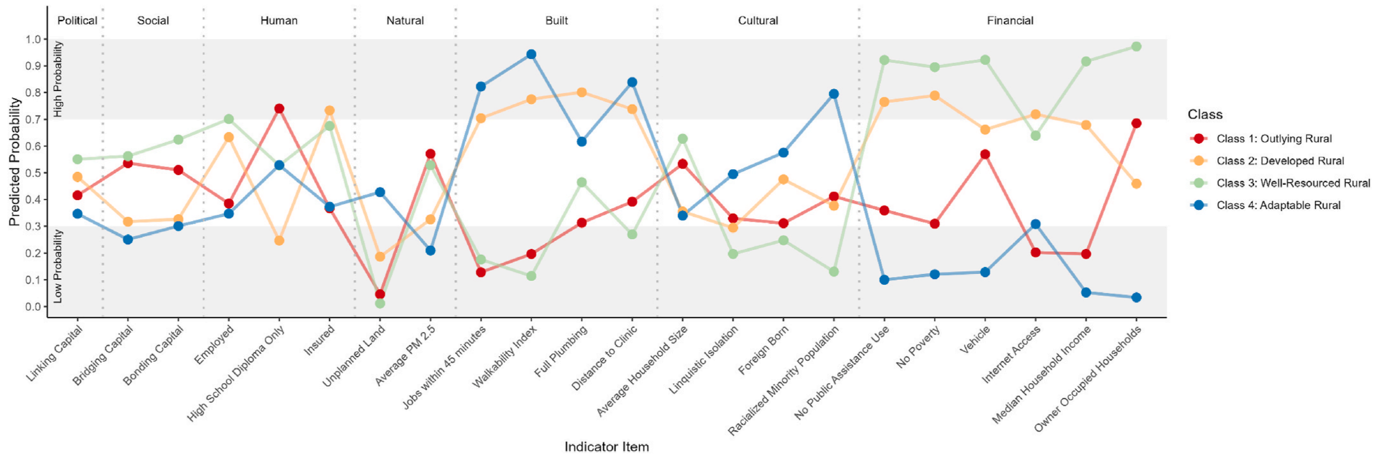
	Rural Class			
	Class 1	Class 2	Class 3	Class 4
	Outlying	Developed	Well-Resourced	Adaptable
Item				
Political				
Linking Capital	0.42	0.48	0.55	0.35
Social				
Bridging Capital	0.54	0.32	0.56	0.25
Bonding Capital	0.51	0.33	0.62	0.3
Human				
Employed	0.39	0.63	0.7	0.35
High School Diploma Only	0.74	0.25	0.53	0.53
Uninsured	0.63	0.27	0.32	0.63
Natural				
Total Unplanned Land	0.95	0.81	0.99	0.57
Average PM 2.5	0.43	0.67	0.47	0.79
Built				
Jobs within 45 min	0.13	0.7	0.18	0.82
Walkability Index	0.2	0.78	0.11	0.94
Lacking Full Plumbing	0.69	0.2	0.54	0.38
Distance to Clinic	0.61	0.26	0.73	0.16
Cultural				
Average Household Size	0.53	0.36	0.63	0.34
Linguistic Isolation	0.33	0.29	0.2	0.49
Foreign Born	0.31	0.48	0.25	0.58
Racialized Minority Population	0.41	0.38	0.13	0.8
Financial				
Public Assistance Use	0.64	0.23	0.08	0.9
Poverty	0.69	0.21	0.1	0.88
No Vehicle	0.43	0.34	0.08	0.87
Internet Access	0.2	0.72	0.64	0.31
Median Household Income	0.2	0.68	0.92	0.05
Owner Occupied Households	0.69	0.46	0.97	0.03

Note: The items in this table are presented as they were entered initially into the model.

Appendix Table C
Differences in mean 2020 CDC/ATSDR Social Vulnerability Index percentile ranking estimates by identified rural classes

	CDC/ATSDR SVI Theme				
	Socioeconomic Status	**Household Characteristics**	**Racial & Ethnic Minority**	**Housing Type & Transportation**	**Overall SVI**
Class 1 (Ref) **Outlying**	0.610 (0.004)[b]	0.594 (0.005)[b]	0.335 (0.005[b]	0.590 (0.004[b]	0.598 (0.004)[b]
Class 2 **Developed**	−0.150 (0.006[b]	−0.052 (0.007[b]	−0.033 (0.007[b]	0.013 (0.006)[a]	−0.089 (0.005)[b]
Class 3 **Well-Resourced**	−0.197 (0.005)[b]	−0.137 (0.006)[b]	−0.120 (0.006)[b]	−0.145 (0.005)[b]	−0.206 (0.005)[b]
Class 4 **Adaptable**	0.067 (0.005)[b]	0.088 (0.006)[b]	0.083 (0.006)[b]	0.167 (0.006)[b]	0.127 (0.005)[b]

[a] $p < 0.05$.
[b] $p < 0.0001$.



Appendix Fig. A. Predicted probability of community characteristics across identified latent classes.

Data availability

All data utilized are publicly available. While the authors do not have the ability to share the data utilized, the sources and measures are well-documented for anyone wanting to replicate. The final rural classification dataset can be found on the Harvard Dataverse (doi.org/10.7910/DVN/NRJXHK).

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