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ORIGINAL PAPER

Where social vulnerability indices diverge: Navigating the decision cascade for local site selection

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Abstract
Social vulnerability (SV) describes how socioeconomic characteristics influence individuals' or communities' ability to prepare for, withstand, and recover from hazardous events. Composite indices, which include multiple indicators to represent SV, are used across national, state, and local policy levels to guide decision makers in allocating limited resources. While several established SV indices (SVIs) exist for the United States, custom-made SVIs have been published across disciplines. Whether using a widely established SVI or custom-made, comprehensive documentation of the choices and assumptions made during the modeling process is often lacking. Often invisible to end-users these decisions have significant implications for SVI output, especially when applied to local site selection. Consequently, they influence resource allocation and our scientific understanding of the determinants, drivers, and consequences of disaster vulnerability. We addressed this issue by documenting and comparing the methodological choices, underlying assumptions, and their implications across multiple phases of SVI modeling for three existing indices. We provide guidance to help navigate the choices and assumptions through data selection and preparation (Phase 1), index construction (Phase 2), and validation and application (Phase 3). We argue that this process—a *decision cascade* in which methodological choices and assumptions influence subsequent phases of SVI modeling—explains differences in SVI scores. To demonstrate the implications based on our decision cascade framework, we applied our methodology to the selection of local study sites in Southeast Texas, where three SVIs diverged. Local knowledge was required to interpret divergent SVI results and inform site selection.

Keywords Social vulnerability · Vulnerability science · Socioeconomic characteristics · Hazard policy · Decision making

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1 Introduction

Disaster risk reduction recognizes vulnerability as encompassing both physical exposure to hazards and the consequence of complex social relations and processes. Understood as social vulnerability (SV), the concept describes how socioeconomic characteristics influence an individual's or community's ability to prepare for, withstand, and recover from hazard events (Wisner et al. 2004). A common approach to measuring SV is to use composite indices with indicators representing characteristics such as race, gender, economic status, and disability (Fatemi et al. 2017). The growing adoption of SV indices (SVIs) by federal, state, and local agencies has elevated SV from a theory to an influential consideration in resource distribution through localized site selection. For example, the Federal Emergency Management Agency (FEMA)'s Community Disaster Resilience Zones (CDRZ) program selected 483 census tracts in 2023 as sites at greatest risk from natural hazards based, in part, on the Centers for Disease Control/Agency for Toxic Substances and Disease Registry Social Vulnerability Index (CDC/ATSDR SVI) (CDC/ATSDR 2022; Cutter et al. 2014; FEMA 2023; Salinas et al. 2023). CDRZ communities then became eligible for increased federal financial aid (FEMA 2023). As SVIs transition from academic tools to decision-making instruments, understanding the methodological choices behind them becomes critical for disaster policy implementation related to mitigation, resilience, or post-disaster recovery.

Over the past two decades, more than 120 distinct SVIs have been developed and applied in at least 91 countries, spanning environmental, disaster, and health fields (Mah et al. 2023; Fatemi et al. 2017; Painter et al. 2024). Our research was motivated by a practical and consequential question resulting from this growth in SVIs: Which SVI should be used, and why, when the goal is local site selection? This core question informed our testable research question: What are the consequences of SVI methodological choices and assumptions for local site selection? In this study, we evaluated these "consequences" by comparing local site selection using multiple SVI rankings. Our attempts to answer these questions revealed a gap in the literature on how SVI-construction decisions are documented and how those choices shape site selection.

Our contribution builds on recent critiques of SVI methodology (Tate 2012; Rufat et al. 2019; Spielman et al. 2020; Enderami and Sutley 2024), which highlight output variation but do not unpack the full decision process and its consequences. Although comprehensive guidance exists for constructing composite indicators in general (OECD et al. 2008; Becker et al. 2022), operational guidance for choosing among competing SVIs for local decisions—and for documenting how methodological decisions map to different site selections—remains limited. To address this limitation, we compared three SVI across three interconnected phases—data selection and preparation, index construction, and validation and application. Throughout this process, modeler decisions—often invisible to end-users—determine which sites are classified as more or less vulnerable, with cascading effects for policy and for theoretical understanding of vulnerability. In this paper, we demonstrate how this decision cascade framework can be applied to systematically analyze the decision points, underlying assumptions, and methodological limitations inherent in SVI modeling. We then demonstrate the implications of our framework via a case study in Southeast Texas, focusing on site selection decisions. This application illustrates that even with careful, transparent application of SVIs, local site selection depends on local knowledge.

2 Literature review

Deeply embedded in social relations and processes, SV extends beyond physical exposure to hazards. SV refers to the differential capacity of individuals or communities to prepare for, respond to, and recover from damage or loss resulting from exposure to a hazard event or series of hazard events (Wisner et al. 2004; Bakkensen et al. 2017; Cutter 2024; Painter et al. 2024). Vulnerable communities are those that are disproportionately harmed by hazard events (Thomas et al. 2009), including higher rates of deaths and property damage and slower recovery compared to less vulnerable communities (Cutter et al. 2003; Van Zandt et al. 2012; Flanagan et al. 2018).

Critical to understanding SV is recognizing that communities and individuals are not inherently vulnerable. To support this perspective, SV frameworks draw from theories addressing disadvantaged communities in the context of hazards or climate change, including environmental justice (Bullard 1994), Black feminism's intersectionality (Crenshaw 1991), climate justice (Caney 2014), and climate equity (Fitzgerald 2022). These theories provide evidence that SV results from a history of marginalization, segregation, and under-investment based on certain social characteristics like race or age, such that some populations experience greater hazard and climate exposure and susceptibility to damage as a result (Jacobs 2019; Hendricks and Van Zandt 2021). These structural inequalities shape differential access to resources across space and time, often placing marginalized populations at greater risk. For example, low-income neighborhoods are more likely to be near toxic land uses and flood-prone areas (Bullard 1994; Fothergill and Peek 2004). Vulnerable communities are often underrepresented in decision-making processes and are underserved as a result (Bohle et al. 1994).

Decades of research documenting inequality in hazard and disaster experience by demographic characteristics led to attempts to create combined models or indices to identify geographic areas of greater need for support before, during, or after disasters. To operationalize SV, researchers and practitioners have developed quantitative tools that aggregate socioeconomic and demographic indicators to estimate this latent construct (Flanagan et al. 2018; Spielman et al. 2020; Cutter 2024). These indices are increasingly used not only to inform our scientific understanding of the determinants and consequences of vulnerability, but also to identify vulnerable communities and guide resource allocation (Cutter et al. 2003; Oulahen et al. 2015).

Studies of SVI often include national (Cutter et al. 2014; Flangan et al. 2018), regional (Bakkensen et al. 2017), and state level (Biggs et al.2020) analysis that provide validation that SVI correlates with disaster impacts. However, studies stop just shy of selecting sites for intervention (Nelson et al. 2015; Oulahen et al. 2015). To our knowledge, no existing paper has detailed the use of SVI for local site selection.

Differences in indices—including built-in assumptions—and validation challenges have led to an array of SVIs with varying strengths, limitations, and applications that can yield conflicting results (Tate 2012; Reckien 2018). As decision makers seek tools to inform site selection for resource distribution, the need to understand the conflicting results increases. We outline a three-phase decision cascade to describe these choices and to explicate the assumptions.

3 The SVI decision cascade framework

SVI models involve a connected series of decisions and assumptions that cascade through three development phases (Fig. 1). These phases are: (1) Data selection and preparation; (2) Index construction; and (3) Validation and application (OECD et al. 2008; Tate 2012). We argue that explicating the underlying assumptions of SVIs helps to understand why SVIs rankings diverge for local site selection. The following sections describe each phase and discuss assumptions made by the modeler in each phase.

3.1 Phase 1: Data selection and preparation

Phase One involves six fundamental choices and seven assumptions about the data that will form the SVI's foundation. The first choice is *indicator selection*—deciding which socioeconomic characteristics to include in the index. Selection may be informed by theory, expert elicitation, literature, surveys, and/or public participation. Once selected, indicators must be operationalized through *data source selection* and *calculation strategies*, typically using data from national sources, such as the US Census Bureau (USCB). After selecting a calculation strategy, SVI modelers must decide how to handle *missing values*—whether to ignore, impute, or drop observations. Missing data arise when a census geography has

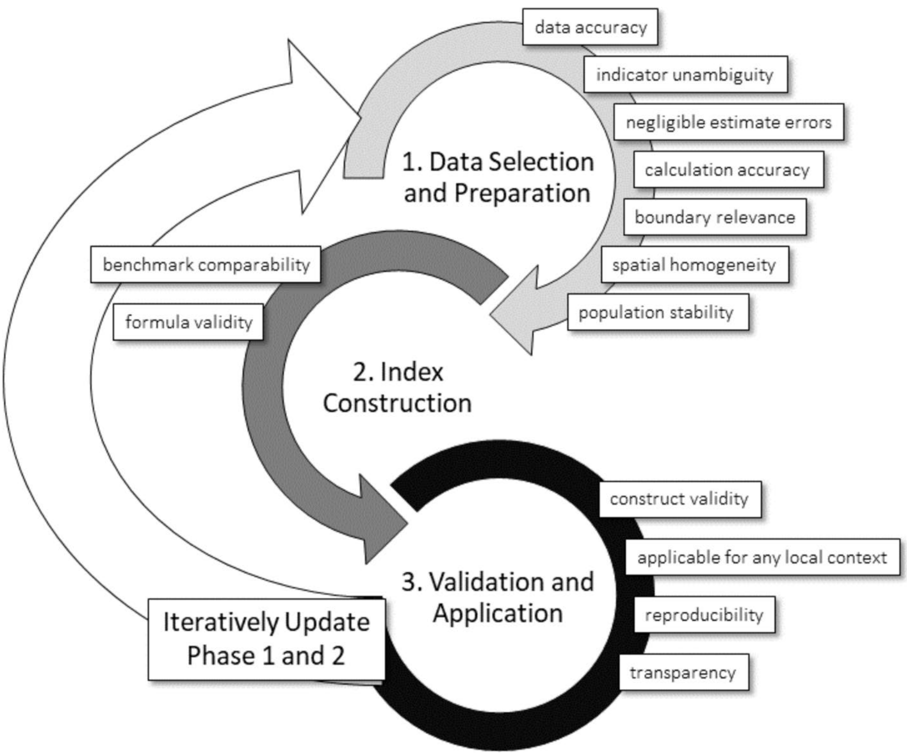

Fig. 1 SVI Decision Cascade Framework across three phases of index modeling showing key assumptions to navigate

no people (e.g., airports or parks) or people without income data (e.g., prisoners or college students). Final choices concern *analytical scale*[1] and *temporal scale*.

During the data selection and preparation phase, SVI modelers must navigate seven critical assumptions: data accuracy, indicator unambiguity, negligible estimate errors, calculation accuracy, boundary relevance, spatial homogeneity, and population stability. The first assumption concerns *data accuracy*. While the USCB employs rigorous methods, data flaws remain. The 2020 decennial census had a 99.98% response rate[2] (Jarmin 2020), but the American Community Survey (ACS) response rates dropped to 71% during the COVID-19 pandemic and recovered to 85% by 2022 (USCB n.d.-a). Non-response patterns are not random and cause differential undercounts among specific populations. O'Hare (2019) documented substantial undercounts among young children (4.6%), American Indians on reservations (4.9%), Blacks (2.1%), and Hispanics (1.5%) in the 2010 Census, with these disparities compounding at intersections of multiple characteristics (Anderson and Fienberg 2001; O'Hare 2019).

The second assumption is *indicator unambiguity*, which means that each concept maps to a single variable or data table from within census data. The USCB's Application Programming Interface (API) provides access to millions of variables organized by subject within tables (USCB n.d.-b 2024), creating significant complexity in how indicators could be operationalized. Third, modelers often assume *negligible estimate errors*, or that margins of error (MOE) for estimates can be ignored. Each ACS estimate includes an MOE that reflects uncertainty (USCB 2009), which increases as sample sizes decrease. Despite knowledge of large MOEs, most modelers disregard them in SVI construction (Spielman et al. 2014; Folch et al. 2023). The fourth assumption made is related to *calculation accuracy*, including that derived estimates have been accurately calculated by the SVI modeler. SVI construction often combines multiple variables. Even minor differences in how these calculations are performed can lead to significant variations in the final index, especially when values are normalized or ranked.

The choice of spatial scale introduces critical assumptions about how vulnerability is mapped and understood. Overall, spatial scale selection influences outcomes through the Modifiable Areal Unit Problem (MAUP), where changing the scale or boundaries of analysis can alter results (Fotheringham and Wong 1991). Therefore, an SVI modeler must assume *spatial homogeneity* and *boundary relevance* and that all administrative boundaries aligned with neighborhood level SV patterns. However, spatial aggregation into census tracts or block groups homogenizes population data, masking internal variation (Rosenheim et al. 2021). To further complicate the issue, SVIs represent aggregated population areas, not individuals, this homogenization can lead to an ecological fallacy—attributing group characteristics to individuals (Wakefield and Lyons 2010). SVI models also assume *population stability*. SVIs rely on residential data, ignoring temporal population shifts. This assumption neglects differences between daytime and nighttime populations and fails to account for transient populations such as students, seasonal workers, or visitors. In areas with sig-

[1] Analytical scales within the US typically include political boundaries (states or counties) or statistical subdivisions of counties defined by census tracts or block groups. Census tracts have an average population of 4,000 people. Block groups are subdivisions of census tracts that contain between 600 and 3,000 people. (USCB 2025).

[2] Response rate includes self-responses (online, phone, and mail), proxy responses provided by neighbors, and enumeration using administrative records (Jarmin 2020).

nificant temporal population variation, vulnerability assessments based solely on residential data may misrepresent actual vulnerability (Amini et al. 2024).

3.2 Phase 2: Index construction

The second phase of the decision cascade generates a composite index based on the prepared data and involves four decisions and two assumptions. The first choice is *index structure*: deductive, hierarchical, and inductive (Tate 2012). Deductive approaches include each indicator directly. A hierarchical index groups indicators into sub-indices that share the same underlying conceptual dimension of vulnerability. The sub-indices are aggregated to create the final index. Inductive approaches, popularized by SoVI®, use techniques like principal component analysis (PCA) to reduce indicators to underlying factors (Cutter et al. 2003).

To combine indicators into one index, modelers normalize them to comparable scales. *Indicator normalization* choices include min–max scaling, percentile rank, or z-scores (OECD et al. 2008). Modelers then decide on *indicator weighting*. Indicator weighting reflects each indicator's relative importance. Approaches to weighting include equal weighting, equal weighting within sub-indices, using expert opinion on the relative importance of one indicator vs another, or using the factor loadings that result from a PCA. *Indicator weighting* within a composite index is a common challenge across disciplines (Saltelli 2007). Social science theory shows that different indicators influence vulnerability in distinct ways and may require some indicators to have larger weights that will increase a vulnerability score. For example, low-income households have fewer resources and may also struggle to access funds for evacuation, repair, or rebuilding after a disaster (Fothergill and Peek 2004; Van Zandt et al. 2012). In contrast, people with access and functional needs may require specialized communication technologies to understand disaster warnings or specialized transportation to evacuate (Davis and Phillips 2009; Stough and Kelman 2018). People living in group quarters—which represent everything from nursing homes to prisons—lack agency to implement mitigation strategies and may be unable to undertake protective actions like evacuation (Brown et al. 2007; Purdum et al. 2021). Once weights have been determined, modelers aggregate the individual indicators. *Indicator aggregation* is how indicators are combined into one score. Methods include additive and multiplicative methods or using arithmetic and geometric means.

During the index construction phase, SVI modelers have two key assumptions to contend with: benchmark comparability and formula validity. First, *benchmark comparability* assumes that the benchmark regions (e.g., state or nation) appropriately contextualize local vulnerability. SVI calculations typically normalize indicators against a benchmark region. The choice of benchmark region can affect which areas appear vulnerable, as noted by Spielman et al. (2020). For example, a census tract might rank as highly vulnerable compared to national averages but show moderate vulnerability when compared to state averages if the state itself has higher overall vulnerability compared to the nation. *Formula validity* assumes that methods for calculating indices produce reliable and consistent estimates. Index construction involves numerous methodological choices about normalization, weighting, and aggregation (Tate 2012). These often lack theoretical justification but can significantly alter results (Rufat et al. 2019; Spielman et al. 2020).

3.3 Phase 3: Validation and application

The final phase of the decision cascade concerns choices related to how the SVI will be tested, interpreted, and applied. We identify two choices and five assumptions within Phase Three. The choice to validate assesses how well the index reflects its intended construct using internal consistency tests, external comparisons with disaster outcomes, or sensitivity analysis. Within *validation*, SVI modelers assume *construct validity*—that index scores meaningfully reflect the inferred SV construct. As Spielman et al. (2020) demonstrated, some indices like SoVI® lack internal consistency, as multiple models using the same data can produce different vulnerability scores for the same area depending on changes in scale or boundaries. Awareness of limits to validity have led to calls for context-specific SVI. For example, organizing by disaster cycle stages can serve to increase index validity, as the drivers of social vulnerability can vary substantially as a function of disaster phase (Rufat et al. 2015; Bakkensen et al. 2017).

The choice of *application* refers to how the index is used in practice and can include resource allocation decisions, hazard mitigation planning, evacuation planning, and implementation of post-disaster recovery operations. While SVI models are generally designed for national or regional use, their users often assume that the results are *applicable for any local context* (FEMA 2023; Salinas et al. 2023)—an assumption that will be particularly salient for local site selection.

After validation and application modelers may find that choices and assumptions are not valid, the SVI modeler will need to iteratively update phases one and two. This iterative process assumes model *reproducibility* and *transparency.* To address issues, SVI modelers need to have clear documentation of how they navigated their choices and assumptions. Reproducibility and transparency improve data reuse and allow for continuous improvements of applications of the SVI concept to hazards research.

The choices and assumptions across the decision cascade provide a framework for exploring how different SVI models influence site selection. In the following sections, we demonstrate how these assumptions manifest disagreements in a comparative assessment of three SVI models applied to Southeast Texas.

4 Methods

As part of a larger interdisciplinary project on hazard resilience, collaborators from four universities and two national laboratories aimed to integrate inequality considerations into assessment of flooding and air pollution risk in the Southeast Texas region. The team also aimed to identify underserved neighborhoods within this region for targeted community-engaged research on adaptation strategies related to these risks. The region was selected for its coastal location and concentration of petrochemical facilities. In this section, we overview the study area and selected SVIs for our analyses.

4.1 Overview of the study area

Texas is considerably impacted by compounding, intersecting, and multi-hazard events. For example, over the past two decades, Texas has been impacted by over $75 billion in flood hazards and extreme heat events. As Winter Storm Uri demonstrated in 2021 across Texas (Glazer et al. 2021), compounding impacts from unprecedented extreme weather events disrupt vital infrastructures. Located along the Gulf Coast near the Texas-Louisiana border, Southeast Texas (SE TX) faces multiple and intersecting hazards, including coastal storms, extreme precipitation, flooding, extreme heat, drought, and wildfires. Our study region, the five-county (Hardin, Jasper, Jefferson, Newton, and Orange) area that encompasses the Beaumont-Port Arthur Metropolitan Statistical Area (MSA), is home to one of the nation's largest petrochemical industrial complexes, which makes the region more likely to experience significant acute air toxins and chronic air toxic exposures that can raise the risk of cancer and other adverse health outcomes (Flores et al. 2023; Jephcote et al. 2021). The Beaumont–Port Arthur area ranks in the top 10% of the most polluted US communities and has a long legacy of air-quality violations (Ge et al. 2021).

In 2020, 443,618 people lived in the five-county region (Fig. 2) (USCB 2020a). The region is demographically diverse: 23% are non-Hispanic Black or African American, 57% are non-Hispanic White, and 15% are Hispanic. Economically, 15.8% of the metro area live below the poverty level, which is higher than the national rate of 12.8% (USCB 2020a). The five counties include 128 census tracts and 367 block groups.

To explore issues related to site selection we selected two sites (West Port Arthur and East Groves) to present in this paper (see Fig. 4). These two sites were part of 20 sites identified through a two-years community engagement process based on local concerns for flooding or air quality (Passalacqua 2024). This process engaged SE TX community members representing leaders in nonprofit organizations, local governments, religious institutions, and businesses through six participatory workshops. The recruitment process and workshops followed an established guide for engaged research (Van Zandt et al. 2020). Our two sites were selected because: (1) they are geographically proximate, allowing for controlled comparison within a similar environmental context; (2) they represent contrast-

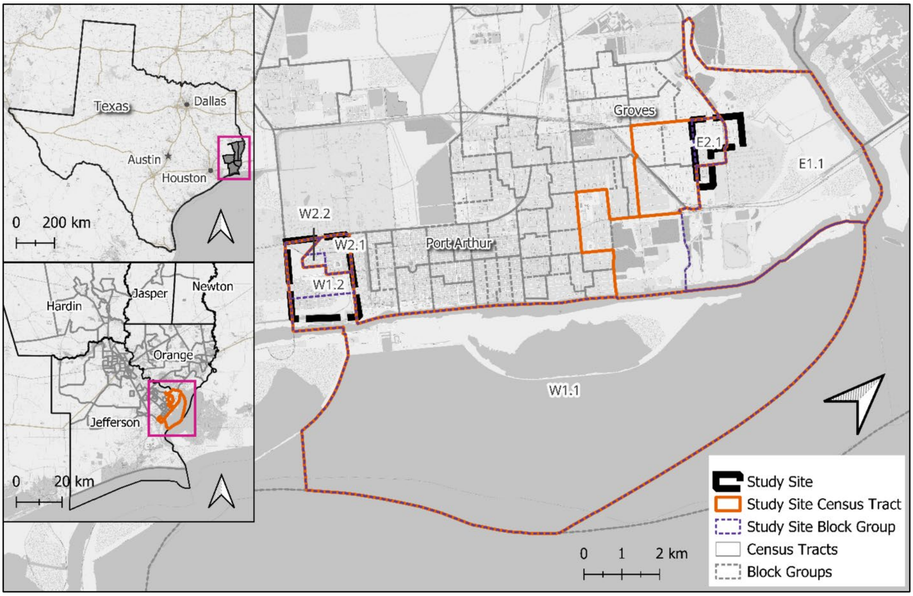

Fig. 2 Map of SE TX region and the study area census tracts, block groups, and selected study sites

ing demographic and spatial characteristics (different population sizes and land areas) that help illustrate how SVIs perform under varied conditions; and (3) they exemplify the SVI disagreement patterns we observed across the broader region. These two sites thus serve as illustrative examples rather than isolated cases, helping us demonstrate the practical implications of methodological choices on site selection.

In 2020, our two example sites overlapped four census tracts (Fig. 2). For West Port Arthur, the total population of the tracts W1 and W2 was 2,538, over a total land area of 11 km^2. The west study site is 4.1 km^2; 31.4% of the land area of W1 and 100% of the land area of W2 fall within the study site. Most of the area of W1 that does not overlap the study site is parkland. By contrast, the two tracts in East Groves (E1 and E2) had a total population 3.7 times larger (9,541) and a land area twice as large (23.6 km^2) (USCB 2020a). The east study site is 1.7 km^2; 3.0% of the land area of E1 and 20.8% of the land area of E2 fall within the study site. For West Port Arthur, the two census tracts include four block groups (W1.1, W1.2, W2.1, W2.2), all of which overlap the study site, so the total population and land area included remains the same. The East Groves study site overlaps with two block groups (E1.1, E2.1) which have a combined population of 1,096 and a land area of 18.6 km^2 (USCB 2020a). The shape of each site was drawn by the community taskforce without reference to census geographic boundaries.

4.2 Selected SVIs

For this analysis, we selected three SVIs that span a range of methodological approaches and institutional origins. The CDC/ATSDR SVI is nationally produced and widely used in disaster management (Flanagan et al. 2018; CDC/ATSDR 2022). The Hazard Reduction and Recovery Center (HRRC) SVI, developed at Texas A&M University (HRRC 2025), was first outlined in Van Zandt et al. (2012) and was validated using post-disaster survey data. SVInsight is a tool developed by researchers at the University of Texas as part of the Planet Texas 2050 initiative and emphasizes context-specific customization for flooding within Texas (Bixler et al. 2021; Preisser et al. 2022). We chose these SVI because they represent a spectrum of methodological approaches and institutional contexts which allows us to test the consequences for local site selection. The CDC/ATSDR SVI serves as a benchmark—it is the most widely adopted SVI in US disaster management and was used in federal programs such as FEMA's CDRZ designation (FEMA 2023). The HRRC SVI and SVInsight represent custom-developed, Texas-specific indices designed to work at both the census tract and block group levels, which overcomes a limitation in the CDC/ATSDR SVI, which only provides census tract level results. The HRRC SVI methodology is like that of the CDC/ATSDR SVI but makes different choices with respect to indicators and aggregation. SVInsight employs an approach like SoVI® (Cutter et al. 2003), which is an SVI commonly used in research applications. Therefore, our selection allows us to compare a national standard against regionally tailored alternatives, demonstrating how different methodological philosophies lead to divergent vulnerability assessments even when applied to the same geographic area.

5 Results

In this section, we explore the choices each SVI makes across the three phases of our decision cascade framework. Within each phase, we first describe the choices the SVI modelers made and then explicate the assumptions within each phase. We provide examples for how methodological choices and assumptions explain the diverging SV scores and how different choices influenced site selection.

5.1 Phase 1: Data selection and preparation

In the first phase of SVI modeling, the three SVIs share similar choices for data source selection and temporal scale while differing in terms of indicator selection, analytical scale, calculation strategies, and missing values (Table 1). All three SVIs use the USCB's ACS for *data source selection* and they all provide SVI values for multiple years. For this study, we selected the 5-year 2020 ACS (2016–2020) for the *temporal scale*. At the *analytical scale*, the CDC/ATSDR SVI provides census tract-level scores, while HRRC SVI and SVInsight provide scores at both tract and block group levels.

Indicator selection was influenced by the subthemes or groups considered. The CDC/ATSDR SVI has an emergency management focus with four subthemes for socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation (Flanagan et al. 2011). The HRRC SVI focuses on disparities in disaster response and recovery (Van Zandt et al. 2012), and groups indicators into five second-order indices for needs associated with childcare, elder care, transportation, temporary shelter and housing recovery, and civic capacity. Conceptually, the HRRC SVI shares 10 indicators with the CDC/ATSDR SVI, but groups them differently. SVInsight adds indicators related to gender, wealth, and employment, but depends on factor analysis in Phase 2 to decide the inclusion, exclusion, and grouping of indicators based on statistical analysis (Bixler et al. 2021; Preisser et al. 2022). Table 2 is organized first by the CDC/ATSDR SVI's groupings to highlight common indicators and differences in SVI perspectives. In total, modelers selected 39 indicators across the three SVIs (Table 2). The three SVIs share only seven of 39 possible indicators, highlighted in Table 2.

Table 1 Phase 1: Data selection and preparation choices across three SVIs

Phase choices	CDC/ATSDR SVI	HRRC SVI	SVInsight
Indicator selection	16	16	27
Data source selection	USCB	USCB	USCB
Analytical scale	Census tract	Census tract and block group	Census tract and block group
Temporal scale	5-year ACS 2016–2020	5-year ACS 2016–2020	5-year ACS 2016–2020
Calculation strategies	Percentage of population	Percentage of population	Percentage of population or absolute value
Missing values	Drop observations	Set to 0	Exclude low population and Spatial interpolation

Table 2 Descriptions of indicators in the three SVIs with 2020 5-year ACS Table IDs and assigned groups

Indicator description	CDC/ATSDR SVI		HRRC SVI		SVInsight	
	Table	Group[a]	Table	Group[b]	Table	Group[c]
Poverty	S1701	1	B17021	4	B17021	1
No high school diploma	S0601	1	B15003	5	B15003	1
Unemployed	DP03	1	B23025	5	B23025	-
No health insurance	S2701	1			B27010	-
Housing cost burden	S2503	1				
English language proficiency	B16005	2	B16004	5	B16004	1
Single-parent households	B11012	2	B11005	1	B11005	-
Civilian with a disability	DP02	2				
Aged 65 or Older	S0101	2	B17017	2		
Aged 17 or Younger	B09001	2				
Minority	DP05	3	B03002	4		
Mobile homes	DP04	4	B25024	4	B25024	-
Population in group quarters	B26001	4	B09019	4		
Multi-unit structures	DP04	4				
Crowding	DP04	4				
No Vehicle	DP04	4	B25044	3	B25044	-
Children under 5 years population			B01001	1		
Elder households in poverty			B17017	2		
Public transportation-dependent households			B08301	3		
Vacant housing units			B25002	4	B25002	-
Renter households			B25033	4	B25003	3 + 5
Housing units older than 20 years			B25034	4		
Hispanic					B03002	1
Population in construction jobs					C24010	1
Median home value					B25077	2
Median gross rent					B25064	2
Households earning over $200 K					B19001	2
Per capita income past 12 months					B19301	2
Households with social security income					B19055	3
Median age					B01002	3
Population under 5 and Over 65					B01001	3 + 4
Population that is female					B01001	4
Female-led households					B11001	4
Females in the workforce					C24010	4
Average household size (People per unit)					B25010	5
Population in service jobs					C24010	-
Native american, not hispanic					B03002	-
Asian, not hispanic					B03002	-
African american, not hispanic					B03002	-
Total variables	16		16		27	

a. CDC/ATSDR Themes: 1. Socioeconomic Status; 2. Household Characteristics; 3. Racial & Ethnic Minority Status; 4. Housing Type & Transportation. b. HRRC SVI 2nd-Order Groups: 1. Child Care Needs; 2. Elder Care Needs; 3. Transportation Needs; 4. Shelter Needs; 5. Civic Capacity Needs. c. SVInsight factor analysis defined groups. All indicators used in initial analysis; hyphens represent indicator exclusion

For *calculation strategies*, the CDC/ATSDR SVI and HRRC SVI convert all indicators into percentages of the population, while SVInsight includes population percentages except for median home value, median gross rent, and average household size, for which it provides absolute values. The choice to convert to percentages may obscure the absolute number of people. For instance, the CDC/ATSDR SVI reported that tract E2 had a poverty rate of 28.9%, almost half that of W2 (55.2%). But, in absolute numbers, E2 had 1,627 people living in poverty, more than twice the 806 people in poverty in W2.

We found that each SVI handles *missing values* differently. The CDC/ATSDR SVI identifies missing values but excludes these observations during the index construction. In application, if a tract is missing one indicator, that tract does not receive a CDC/ATSDR SVI score; this generally applies to tracts with only group quarter populations. The HRRC SVI assigns zero to missing values. SVInsight excludes observations with fewer than 75 people and areas without households that may have unreliable estimates. SVInsight applies spatial interpolation for missing indicators. Without interpolation of missing values, factor analysis would not calculate a composite score. The CDC/ATSDR SVI and SVInsight do not calculate SVI scores for three tracts in SE TX. These include two tracts with large prison populations (10,013 people) in Jefferson County and the regional airport with no population. The HRRC SVI calculates low SVI scores for the two tracts with prisons and gives a zero value for the tract with no population. SVInsight interpolates missing median gross rent or median home values for five tracts and 154 block groups across SE TX. For the six block groups in our study site, SVInsight interpolates median gross rent for W1.1, W1.2, and W2.2, and median home value for W1.1, W1.2, W2.2, and E1.1.

During the first phase of SVI modeling, the three SVIs navigate the key assumptions in different ways. While none of the SVI models explore issues with *data accuracy*, we found that the self-response rates for the 2020 decennial census were 34.7% (W1), 54.9% (W2), 51.9% (E1), and 62.4% (E2), compared to an average of 62.1% for Texas (USCB 2020b). Given the temporal overlap with the selected SVI data source, *data accuracy* could be limited given the low response rates, especially for the west study sites. Table 2 shows that across all 39 possible indicators, no single indicator uses the same ACS table in all three SVIs, a clear demonstration of the limitations of the *indicator ambiguity* assumption. For example, we compared poverty across the three SVIs. While all three SVIs include a poverty indicator, they define and calculate it differently. The CDC/ATSDR SVI calculates the percentage of individuals below 150% of the poverty line using table S1701, while the HRRC SVI and SVInsight use table B17021 to calculate the percentage of individuals below the poverty level. Figure 3a shows how these choices result in different tract-level poverty estimates. In our study sites, CDC/ATSDR SVI reported that the East Groves Site would have poverty rate between 28.9% (E2) and 65.5% (E1), and the West Port Arthur Site between 46.9% (W1) and 55.2% (W2). SVInsight and HRRC SVI reported that the East Groves Site would have poverty rate between 10.4% (E2) and 39.2% (E1) and that the West Port Arthur Site between 21.5% (W1) and 47.5% (W2). These discrepancies highlight how the *indicator unambiguity* assumption can lead to different conclusions.

Another complication in *indicator unambiguity* arises from how data are transformed. For instance, correlations for the single-parent household indicator were 0.92 between CDC/ATSDR SVI and HRRC SVI and 0.85 between HRRC SVI and SVInsight (Fig. 4). These differences reflect how each SVI defines and calculates the indicator. CDC/ATSDR SVI includes only households where the householder has no spouse or partner and the chil-

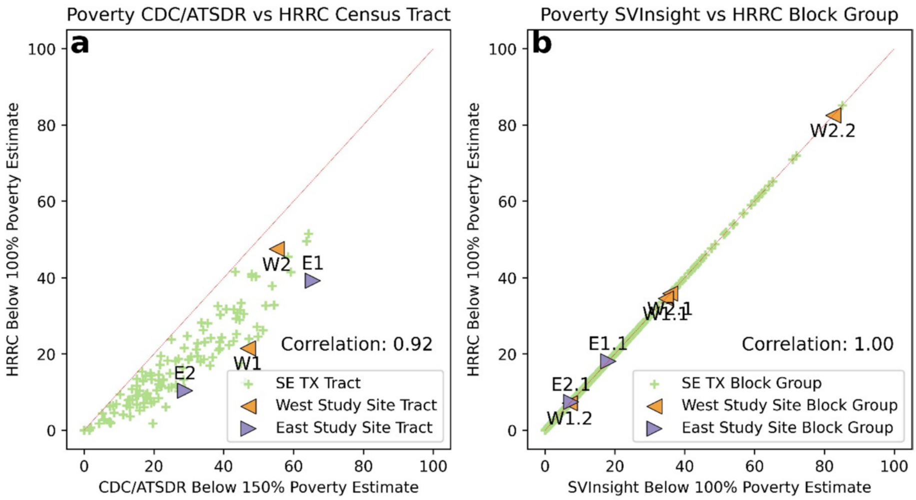

Fig. 3 Scatter plots comparing correlations for indicators related to poverty at the census tract (**a**) and block group geographic scales (**b**)

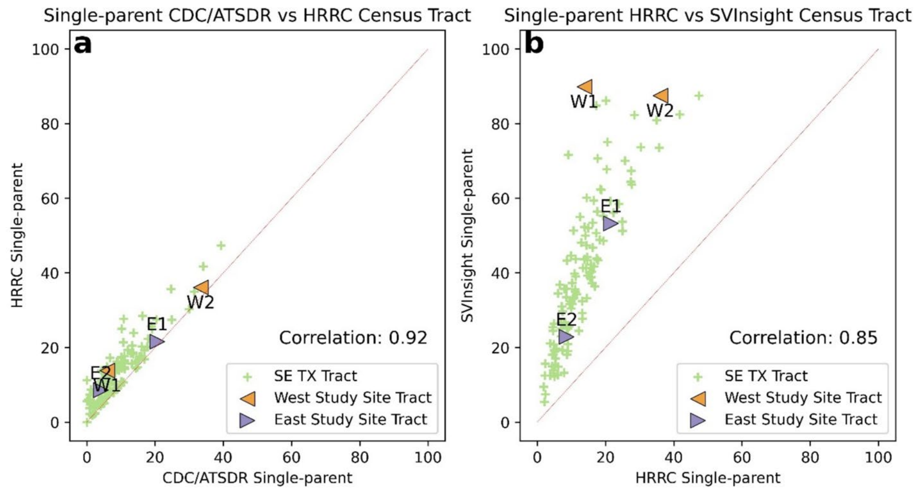

Fig. 4 Scatter plots comparing correlations for indicators related to single-parent households

dren under 18 are the householder's own children. HRRC SVI and SVInsight casts a wider net to include single-parent households with any children. HRRC SVI uses all household types as the denominator, while SVInsight limits the denominator to family households only. These definitional and computational choices result in substantial variation in indicator values, as shown in Fig. 4. Because both the HRRC SVI and the CDC/ATSDR SVI use total households as the denominator, differences in the single-parent indicator arise from the numerator. The HRRC SVI defines single-parent households more broadly by including households with any child under 18, such as single-grandparent households, which can result in higher estimated percentages. In our study sites, CDC/ATSDR SVI reported that the East Groves Site had between 0.04% (E2) and 20.6% (E1) single-parent households and that the West Port Arthur Site between 0.06% (W1) and 33.4% (W2). SVInsight reported the East Groves Site would have between 22.9% (E2) and 53.2% (E1) and that the West Port Arthur Site between 87.5% (W2) and 89.9% (W1) single-parent families.

All three SVIs assume *negligible estimate errors*. However, we find that statistical uncertainty in ACS data warrants consideration for our study sites (additional data are given in Online Resource 1). Although some indicators show slightly higher percentages, the west and east study sites are compositionally similar. Only three indicators show notable differences between tracts at the 90% confidence level. Tract E1 has significantly higher percentages of residents without a high school diploma (26.6–43.0%) and with limited English proficiency (9.1–20.1%). Tract E2 has a significantly lower percentage of minority residents (26.5–50.9%).

Early in our comparison of the three SVIs, we tested the assumption of *calculation accuracy* by looking at correlations between commonly shared indicators. During this process, we found multiple discrepancies, including changes in how USCB numbered variables between the 2018 and 2020 ACS for group quarters and double counting Hispanic populations when calculating individual race/ethnicity categories. These calculation issues were communicated to the SVI modelers and fixed before the analysis was completed.

As described in Sect. 4.1, the shapes of the study sites overlap the census geographies in irregular ways. For the community taskforce, the study sites were drawn to reflect neighborhoods of interest. The mismatch in the overlap calls into question the assumption of *boundary relevance* for the census geographies. For example, tracts W1 and E1 have large land areas (10.0 and 22.6 km2) that are roughly 90% open parkland or industrial. Using block groups helps to improve the *boundary relevance* and reveals the assumption of *spatial homogeneity*. To explore the assumption of *spatial homogeneity*, we looked at the block group-level data for poverty. Figure 3b shows that tract W2 has a poverty level of 47.5%, but its block groups range from 35.9 to 82.5%. Similarly, tract E1 has a poverty level of 39.2%, while block group E1.1 reports just 18.1%. These indicator differences illustrate the MAUP and underscore how the choice of geographic scale—driven by assumptions about *boundary relevance* and *spatial homogeneity*—can significantly alter SVI outcomes.

The last assumption to explore for Phase 1 is the assumption of *population stability*. ACS data is based on household surveys and reports numbers for people that reside within the census boundaries. The ACS data does not reflect details on people that spend substantial amounts of time in the area at school or work. For our study sites, it is important to note that there is an elementary school and a middle school in the west site and there was an elementary school in the east site until 2023.

In the first phase of SVI modeling, the three indices show signs of potential differences in site rankings despite all selecting data from the USCB 2020 5-year ACS. Differences in indicator selection, calculation strategies, estimate errors, boundary relevance, and analytical scale launch the decision cascade, as shown with our two example study sites. The divergence deepens as the indicators are aggregated into composite scores.

5.2 Phase 2: Index construction

After selecting and calculating individual indicators, the three SVIs adopt different index construction methodologies: index structure, normalization, indicator weighting, and indicator aggregation (Table 3). For *index structure,* the CDC/ATSDR SVI uses a non-hierarchical deductive structure; HRRC SVI employs a hierarchical structure with multiple levels of vulnerability measures; and SVInsight uses an inductive approach based on factor analysis. For *indicator normalization,* the CDC/ATSDR SVI and HRRC SVI calculate percentile ranks for each indicator, while SVInsight applies min–max scaling. SVInsight also inverts three indicators—per capita income, households earning over $200 k, and median home value—assuming they negatively correlate with SV. These *indicator normalization* methods require that each observation be compared with all other observations within the *benchmark region*, all three SVI use Texas as the benchmark region.

Approaches to *indicator weighting* differ substantially. The CDC/ATSDR SVI applies equal weighting to all indicators. The HRRC SVI weights second-order indices equally, which implicitly gives more weight to indicators in groups with fewer indicators. By contrast, SVInsight uses factor analysis to generate weights for each indicator.[3]The last decision in the index construction phase is *indicator aggregation*. CDC/ATSDR SVI calculates the percentile rank of the sum of percentile ranks across the benchmark region. The HRRC SVI uses reranked mean percentile scores of the second-order indices normalized across the benchmark region. SVInsight employs factor analysis scaled 0 to 1, normalized across the benchmark region. These differing approaches to index construction cascade into divergent vulnerability rankings.

Spatial clustering of indicators with skewed statistical distributions also influences *indicator normalization* (Schmidtlein et al. 2008; Nelson et al. 2015). Mobile homes and group quarters illustrate this issue, as they are often restricted by local zoning, leaving many areas without any of these residence types. These patterns are true in SE TX. Across the 128 census tracts in SE TX, 25% have no mobile homes and 50% have no group quarters. For tracts without these indicators, the percentile rank is zero and the next percentile rank is highly skewed. For mobile homes, the percentile ranks start at 44.5 with an average of 76.5. For group quarters, the percentile ranks start at 60.6 with an average of 81.4. For our study sites, W1 has a lower SV score partly because it lacks mobile homes, group quarters, and multi-unit structures. Even small differences in the presence or absence of these indicators can significantly affect percentile ranks when equal weighting is applied. For instance, tract

Table 3 Phase 2: Index construction choices across three SVIs

Phase choice	CDC/ATSDR SVI	HRRC SVI	SVInsight
Index structure	Deductive	Hierarchical	Inductive
Indicator normalization and benchmark	Percentile rank across Texas	Percentile rank across Texas	Min–max scaling across Texas
Indicator weighting	Equal weighting	Equal weighting within sub-indices	Factor loadings
Indicator aggregation	Percentile rank of the sum of percentile ranks across Texas	Reranked mean percentile scores of the 2nd-order indices normalized across Texas	Factor analysis scaled 0 to 1 normalized across Texas

[3] Factor analysis reduces the number of indicators by retaining the most influential ones, applying loading factors, combining the retained indicators into groups, and assigning loading factors to each component group (Preisser et al. 2022).

E2's 1.5% group quarters has a percentile rank of 82.1—comparable to W1's poverty rate of 47%.

To test *indicator weighting* and *aggregation,* we applied the CDC/ATSDR SVI method to the other two SVI. In doing so, we found that for the HRRC SVI, a shift from a hierarchical to deductive structure had only a small effect. The correlation between the two options was 0.98 for SE TX. For SVInsight, the shift from inductive to deductive made a significant difference. The correlation between the inductive and deductive SVInsight options was 0.80, and the correlation with CDC/ATSDR SVI increased from 0.63 to 0.90. Exploring the structural changes for our study sites highlighted that the largest resulting change in SVI score was with SVInsight for tract W2 and specifically for block group W2.1. For tract W2, the shift in weighting and aggregation for SVInsight changed the SVI score from 37.7 to 89.4, and for block group W2.1, the SVI score increased from 50.2 to 93.5.

These differing approaches to index construction cascade into divergent vulnerability rankings. The evidence shows how the assumption of *formula validity* is limited when the choices made during index construction can have significant influence on SVI scores. The combination of structure, normalization, weighting, and aggregation decisions determines which sites emerge as priority areas of potential need under each SVI. The next phase provides a means to validate the choices made in the first two phases.

5.3 Phase 3: Validation and application

Phase 3 focuses on choices for validation and application. All three SVIs include documented validation efforts supporting their assumption of *construct validity*. The CDC/ATSDR SVI was empirically validated through multivariate regression and found to best explain property damage and disaster-related fatalities (Bakkensen et al. 2017). The HRRC SVI was validated during its development using household survey data from Hurricane Ike (Van Zandt et al. 2012). SVInsight was validated through comparison to a 2D physics-based flood model (Preisser et al. 2022). The CDC/ATSDR SVI and HRRC SVI have been applied in decision making and policy contexts. The CDC/ATSDR SVI has been used in research (Biggs et al. 2020) and to prioritize government funding (FEMA 2023; Salinas et al. 2023). The HRRC SVI has been used in evacuation planning for the Texas Gulf Coast (Peacock et al. 2016, 2020). These applications often assume the SVI is *applicable for any local context*. Although all three SVIs acknowledge the potential for indicator modification (Flanagan 2011; Preisser et al. 2022; Van Zandt et al. 2012), none have been modified for use in specific places.

To promote validity and reliability, SVIs should include clear documentation of their methods and any subsequent changes. Such documentation enhances the *reproducibility* and *transparency* of SVI modeling. The CDC/ATSDR SVI includes well-documented metadata, and the FindSVI R package supports replication (Xu et al. 2024). The HRRC SVI provides metadata but lacks code for replication. SVInsight has a GitHub repository with documentation and code for reproducibility (Preisser et al. 2025).

SVIs should also be updated as underlying data or population trends evolve. The CDC/ATSDR SVI has undergone multiple updates, with publicly available records documenting corrections and revisions (CDC/ATSDR 2022). The HRRC SVI was updated in 2017 to reflect population trends, replacing "Households with No Telephone" with "Households

Table 4 Comparison of SVI scores for two study sites in Port Arthur, Texas (2020 5-year ACS SVI values)

	SVI Score						Average SVI Score			
SVI							West	East	Difference	Higher-Ranking Site
Census tract	W1		W2		E1	E2				
CDC/ATSDR SVI	44.2		75.6		96.5	55.8	59.9	76.1	−16.3	East
HRRC SVI	51		83.5		91.9	38.2	67.3	65.1	2.2	West/East
SVInsight	71.1		37.7		82.8	63.9	54.4	73.4	−19.0	East
Block group	W1.1	W1.2	W2.1	W.2.2	E1.1	E2.1				
HRRC SVI	69.2	44.5	85.9	89.3	31.7	45.5	72.2	38.6	33.6	West
SVInsight	77.3	62.1	50.2	86.7	95.2	48.4	69.1	71.8	−2.7	East/West

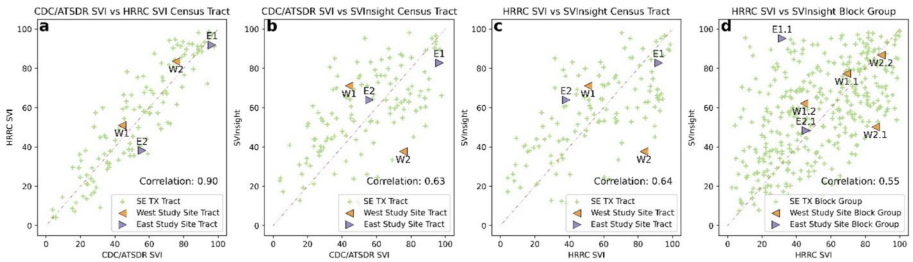

Fig. 5 Scatter plots comparing SVIs at the census tract and block group levels

without Broadband Internet Access." Additionally, both the HRRC SVI and SVInsight were reviewed and updated in response to findings from this paper's analyses.

Table 4 presents the overall SVI scores for the tracts and block groups overlapping the two study sites. For each SVI, we present the final scores by showing the ranked values on a scale of 0 to 100 and by averaging the relevant spatial units to compare which site ranked higher. At the tract level, the east ranked more vulnerable using the CDC/ATSDR SVI and SVInsight, whereas the HRRC SVI showed the two sites as nearly equal. At the block group level, the west appeared significantly more vulnerable according to the HRRC SVI, while SVInsight showed the two sites as equally vulnerable.

This lack of agreement among the three SVIs illustrates a broader pattern observed throughout our study region. As shown in Fig. 5, scatter plots comparing the SVIs at both tract and block group levels reveal weak correlations. Figure 5a compares the HRRC SVI and CDC/ATDSR SVI, which have the strongest correlation (90%). Figure 5d compares the HRRC SVI and SVInsight at the block group level, which have the weakest correlation (55%). Differences in SVI scores for individual tracts and block groups help explain some of the variability in correlations. For example, while HRRC SVI and CDC/ATSDR SVI scored tract W1 as less vulnerable than tract W2, SVInsight has opposite results. A similar difference in scores was found for block group E1.1. The HRRC SVI found E1.1 to be the least vulnerable, but SVInsight found E1.1 to be the most vulnerable. These differences provide evidence for the need to test the validity of SVI scores before application to a particular context.

The intention of SVI is to provide policymakers a tool to make decisions as to which areas should be prioritized for disaster-related resource allocation, such as additional evacuation support from local responders or additional mitigation funding from state or federal resources. In the case of this study, the study site with higher vulnerability would be selected and research funds would be allocated to that area. The study site would be a focus for community engagement efforts, air quality monitoring, and in-depth flood mapping. If our team had selected the census-tract level CDC/ATSDR SVI or SVInsight, the east study site would have been prioritized. If our team had selected the HRRC SVI at the census tract level, we would have considered both sites equally vulnerable, with the west study site being slightly more vulnerable. If our team had selected the HRRC SVI at the block group level, the west study site would have been clearly identified as the most vulnerable area. Finally, if we had selected SVInsight at the block group level, both sites would have been equally vulnerable, with the east side being slightly more vulnerable. The east study site would have been selected in two out of five cases. If we had only looked at one SVI option, we would have missed the variability and overlooked the uncertainty in SVI models. During the project's community engagement efforts, the community members identified the West Port Arthur Site as significantly more vulnerable and selected it as the area of focus for further research.

6 Discussion

SVIs play an important role in characterizing socioeconomic vulnerability differences across large regions and hazard areas. Importantly, they provide a way to integrate established findings about population disparities throughout the emergency management cycle (Cutter 2024). Like most composite indicators, SVIs are useful for showing variation in population vulnerability across parts of a large city, state, region, or nation (Saltelli 2007; Fatemi et al. 2017). When combined with geospatial measures of hazard exposure such as flood risk or industrial pollution, SVIs underscore theory and confirm findings that disaster outcomes are not solely due to environmental hazards, but are instead shaped by how society has historically concentrated particular population groups (e.g., through historic racial segregation) or types of structures (e.g., low-value housing) in areas with greater hazard exposure (Fothergill and Peek 2004; Hendricks and Van Zandt 2021). Data that provide building-level predictions of census demographics have been shown to reduce the number of assumptions inherent in SVI modeling (Rosenheim et al. 2021).

The growing interest in and use of SVIs, though, warrant detailed investigation of their validity and reliability. SVIs are not without their critics. We add to previous research that highlights how differences in index construction and index validation have resulted in an array of SVIs with varying, often unclear applicability (Tate 2012; Bakkensen et al. 2017; Rufat et al. 2019; Spielman et al. 2020). In this paper, we demonstrate that, while generally statistically correlated, there can be low agreement between differently constructed indices for site selection. We have provided evidence that no single methodological choice or assumption explains diverging SV scores for our study sites. Accordingly, the Results highlight a subset of decisions with observable effects on site selection, while other decisions are discussed to illustrate how untested assumptions propagate through the decision cascade. Instead, each decision and untested assumption cascades through the phases of index modeling. SVI construction is complex; final values can be quite sensitive to the methodological details described in our decision cascade framework. If populations that are systematically underrepresented in the underlying data are also those experiencing higher social vulnerability, these sensitivities may result in the systematic underestimation of vulnerability in some communities.

After this detailed analysis, we return to the original question posed by the interdisciplinary team and community partners: “Which SVI should we use?” For program and policy applications, we recommend selecting the simplest and most widely used SVI available to obtain a broad regional picture of the range of SV.

This recommendation emerges directly from our empirical analysis, which shows that simpler index structures make the consequences of methodological choices more transparent. Increasing complexity in index construction amplifies sensitivity to assumptions and obscures why site selection outcomes differ across SVIs. Transparency facilitates comparison across SVIs and clarifies when site selection outcomes are driven by modeling assumptions rather than underlying vulnerability patterns.

Simplicity also enables public interrogation of an SVI’s strengths and weaknesses. It supports community engagement and feedback to validate results for the local context and helps ensure that complex social science metrics can be interpreted across disciplines. For example, the most widely used (and simplest) SVI in the US is the CDC/ATSDR SVI. We also acknowledge that, in our case study, the CDC/ATSDR SVI would have prioritized the east study site whereas community-engaged processes identified the west site as the focus area. Therefore, simplicity is intended as a diagnostic baseline within the decision cascade, not as a final rule for local site selection. The following recommendations reflect considerations of transparency and interpretability for community-engaged site selection, rather than claims of universal methodological superiority.

Using our phased process as a guide, we recommend modelers use the CDC/ATSDR SVI as a baseline, confirm that their models have perfect correlation of indicators at the tract level, and ensure that the same table and formula work at the block group level. Then, modelers should use percentile ranking and the straightforward additive aggregation method as a comparison to more complicated choices. In contexts in which specific aspects of SV are needed that are not included in the CDC/ATSDR SVI, modelers can work from the baseline to construct a custom index that adds those measures. Development of custom indices requires understanding of each phase of the decision cascade we outline, including theoretical understanding of why demographic factors matter for SV (Thomas et al. 2009). Thus, we highly encourage involving a demographer or a social scientist experienced in SVIs who also has detailed understanding of census data and index construction methods. Modelers should communicate all choices, test assumptions, and document all steps in the process of index construction, which is imperative to good science.

7 Conclusion

The decision cascade framework advances existing critiques of SVIs by providing a systematic way to document and analyze how methodological choices and untested assumptions accumulate and interact across the phases of SVI modeling. Tracing how decisions propagate sheds light on why SVIs produce divergent results. Our community-engaged application of multiple SVIs provides a foundation to improve future research into how socioeconomic characteristics influence an individual's or community's ability to prepare for, withstand, and recover from hazard events. Had a single SVI been used for site selection, this opportunity to evaluate how and why indices diverge would have been missed.

Using SVIs to study regional-level patterns is well warranted when indices have been appropriately validated. However, applying any single SVI to local site selection is not advised. SVIs that rely on USCB ACS data inherit shared data limitations and must navigate millions of variables. In practice, transparent and reproducible documentation of modeling choices enables iterative revision, critical evaluation, and comparison across indices. Community-engaged research functions as a necessary mechanism for interpreting and contextualizing SVI outputs. These conclusions do not suggest that SVIs are inappropriate for local site selection, but rather that their use requires explicit consideration of methodological assumptions and incorporation of local knowledge. At the end of the decision cascade, local knowledge was required to overcome SVI limitations. This outcome illustrates that methodological choices and assumptions materially shape how vulnerability is understood and where resources are ultimately directed.

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Declarations

Conflict of interests The authors have no relevant financial or non-financial interests to disclose.

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