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Boundary crossing for urban community resilience: A social vulnerability and multi-hazard approach in Austin, Texas, USA

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ABSTRACT

Natural hazard exposure in urban communities continues to increase, driven by changes in land use, climate, and demographics. Socially vulnerable populations disproportionately inhabit hazard-prone areas, are more sensitive to significant impacts, and have less capacity to cope with socio-natural disasters. One approach to address the challenges of increasing urban hazard risk is to connect hazard scientists and disaster risk reduction practitioners through multi-hazard risk assessments. Based on research and practice in Austin, Texas, USA, this paper presents a methodology for a multi-hazard risk assessment that combines exposure to multiple natural hazards (flood, wildfire, and extreme heat) and social vulnerability. Our approach generated normalized quantitative indicators and geospatial maps that identify neighborhoods where relatively high hazard exposure and sensitivity converge to create risk reduction priority areas. The multi-hazard risk assessment connected researchers across traditional silos and the maps catalyzed academics-city staff-community group communication and collaboration. In addition to presenting the methodology and results of the multi-hazard risk assessment, we reflect on how the process and the maps operated as boundary objects giving rise the co-production between hazard scientists and disaster risk reduction practitioners. We suggest the intersection of co-production and multi-risk assessments We report on the multi-hazard assessment methodology and the implications for urban community resilience co-production.

1. Introduction

Research on urban resilience and urban systems has exponentially increased in recent years [1]. This includes advancements in the fields of urban ecology [2], urban social-ecological systems [3], and hazard and risk reduction [4]. Trends globally highlight the importance of understanding urbanization and climate change as converging issues that create multifaced challenges that span multiple scales [5]. Climate-related hazards – flood, wildfire, extreme heat, among others – have significant impact on lives, livelihoods, and infrastructure. Frequently, those most affected are the most vulnerable in society. Climate change is likely to further increase the exposure in cities to multiple hazards by affecting the magnitude, frequency and spatial distribution of disastrous events [6–8]. The possibility of cascading or domino effects amplify the overall risk and present challenges to community resilience.

The science and modeling of natural hazards has improved tremendously over the past few decades alongside advancements in measurement and computing capacity [9]. However, significant gaps remain between the tools governmental agencies use, the tools and information needed by communities, and those designed by scientists and engineers [10–12]. Despite the promise of improved decision-making and understanding through the use of integrated or coupled models, in practice the use and adoption of model-based decision support systems into regular management policy and practice has not kept pace. Better integration between natural hazard science and hazard risk reduction can improve management and reduce disaster risk [13].

One approach to better support disaster risk reduction decision-making is more comprehensive assessment of the range of hazard types, and the multi-hazard relationships, that can occur in a given place [13,14]. A recent review suggests that single hazard assessments remain the dominant approach [15] even though it is widely acknowledged that

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cities, communities, and neighborhoods face multi-hazard risks compounded with social vulnerability [9,13,16]. Multi-hazard risk information can facilitate a more integrated and less fragmented interaction between scientists, municipal staff and community members [17,18]. Linking research to practice through co-production is key to generating actionable knowledge to decrease exposure, reduce sensitivity, and/or increase adaptive capacity, which are all levers to reduce community vulnerability [19]. Multi-hazard risk mapping can serve as a co-production activity and an "object" to cross boundaries between disciplinary and science/policy/practice boundaries.

Based on research in Austin, Texas, USA, we report the findings of a multi-hazard risk assessment that models three distinct hazard exposures – flood, heat, and wildfire – and combines that with an Austin specific social vulnerability index. This effort was collaborative between academic researchers and city staff with a decision-support objective in mind. Our contributions are two-fold. First, our multi-risk index contributes to a small, but growing, number of studies that combine technical modeling of community hazard exposure with social vulnerability [20–22]. Examples of this in a multi-hazard context are limited (but see Refs. [23,24]. Second, our collaborative approach with researchers and city staff produced a series of maps. We discuss how this is an example of "mode 1" co-production typified by academic and non-academic stakeholders jointly researching solutions [25], and how the maps that are generated become a co-production boundary object that catalyze additional co-production efforts.

1.1. Study area

Austin is an economically diverse and growing city in central Texas at the edge of the Edwards Plateau and the Texas hill country. The 11th-largest city in the United States, Austin has an estimated population of 1,026,833 residents in 2021. The Austin Metropolitan Statistical Area (MSA), as defined by the U.S. Office of Management and Budget, includes five counties (Bastrop, Caldwell, Hays, Travis, and Williamson) and over 2 million people, making it the 29th largest metropolitan area in the United States. Robust population and economic growth since 2000 have increased the tax base and made Austin an attractive city for technology start-ups and established corporations alike. Major technology companies such as Facebook, Google (developing a 35-story downtown office building), Apple (investing $1 billion USD in a new campus), Tesla (building a >$1B USD Cybertruck factory), and Oracle (moving its headquarters) have tens of thousands of workers in Austin collectively. Economic opportunities are matched by increasing challenges like housing unaffordability, inequitable access to services and infrastructure driven by neighborhood displacement, and increasing consumption of water and land. This is compounded by climate forecasts that point to a higher intensity flood-drought regime in the region. Climate models show that average temperatures are increasing, the risks associated with extreme temperatures are more pronounced, and precipitation patterns are shifting, with an increase frequency in heavy precipitation and droughts [26].

Historically underserved and economically marginalized communities are disproportionately impacted by extreme weather [27]. As with many major U.S. cities, Austin's history of economic and housing segregation and broader systemic racism continues to shape the community's resilience to climate related hazards such as heat waves, flooding, and wildfires. Socially vulnerable residents - typically residing in a geography referred to as the "eastern crescent" of the northeast, east and southeast portions of Austin - are already stressed by limited resources, growth pressures, and higher rates of chronic disease. These social and institutional conditions define differential sensitivities and increase the potential for negative consequences in certain Austin neighborhoods.

2. Multi-hazard risk, social vulnerability, boundary objects and co-production

2.1. Multi-hazard approaches

As climate extremes continue to intensify, significant attention has been focused on disaster risk in all its dimensions [28]. Understanding disaster risk is the first priority for action under the UN Sendai Framework for Disaster Risk Reduction ("Sendai Framework") and characterizing multi-hazard risks is an explicit focus [28]. One approach is to develop frameworks for multi-risk assessments [29] or connected extremes [30]. These concepts emphasize the increasing likelihood of climate-related compound events, which are nonlinearly influenced by non-physical factors such as exposure and vulnerability and cut across decision-making levels from household, neighborhoods, informal and formal governance networks, and across society.

Referred to as interacting, cascading, or multi-risk hazards [31], this framing emphasizes the interacting physical and social factors that cause their impacts to be amplified relative to the same hazard occurring separately [30]. Characterizing multi-hazard exposures requires the selection and computation of spatially explicit hazard exposure scores for selected climate-related hazards followed by a linear or multiplicative aggregation of each of the hazard specific exposures [29,32].

However, much of the multi-hazard research comes out of civil and structural engineering and is applied to critical infrastructure, such as bridges [15] with limited interaction between hazard scientists and those implementing disaster risk reduction strategies [13]. Understanding the impacts of cascading hazards on infrastructure is critical for technical urban resilience planning, but fails to inform of the multi-hazard risks to communities and residents. A pivot toward understanding community vulnerability by characterizing hazard exposure, community sensitivity, and adaptive capacity is necessary for addressing social, environmental, and technical challenges of hazards [33]. To assess community vulnerability, it is necessary to measure the sensitivity of the population to hazard exposure. Social vulnerability is one such approach.

2.2. Social vulnerability

Vulnerability represents the predisposition of a community, system, or asset (in our case, a neighborhood) to be adversely affected by a certain hazard. Social vulnerability is a measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards [34]. It is necessarily a multidimensional construct that varies across time and space. Its temporal and spatial heterogeneity is influenced by socio-demographic variables such as income, education, occupation, household composition, home ownership, minority status, gender, age (elderly and children), housing tenure, and vehicle access (Cutter and Finch 2008; [35–38].

Reducing social vulnerability can decrease both human suffering and economic loss [36]. Since the late 1990s, it has generally been acknowledged that a holistic assessment of risk needed to include socioeconomic and demographic factors [34,36,39–41]. The Social Vulnerability Index (SoVI®), created by Hazards and Vulnerability Research Institute at the University of South Carolina [34], is the most frequently cited tool for estimating social vulnerability in the United States. The original calculation of the social vulnerability index [34] synthesized 42 socioeconomic and built environment variables to quantify the social vulnerability to environmental hazards and generate a comparative metric that facilitates the examination of the differences between U.S. counties. After modifications and omissions over time, the newest version (SoVI® 2010–14) contains 29 variables.

Although quite broadly applied in disaster risk reduction scholarship, the integration of measures of social vulnerability with measures of hazard exposure some somewhat nascent (except for [21,22,24]. Social vulnerability has also come under critique in a variety of ways as of late and strategies to ground truth and/or co-produce social vulnerability measures with residents is increasing [42–44].

2.3. Boundary objects and co-production in a hazards context

Boundaries, as a metaphor, are used to describe the relationship between science, policy, and practice [45,46] and are the foundation of strategies that co-produce knowledge between academics and non-academics [47]. Effectively crossing these boundaries is key to addressing the known barriers of knowledge use: lack of credibility, legitimacy, and relevance to decision making [48]. Studies of boundary work demonstrate that scientific knowledge is not inherently credible, but rather its legitimacy is grounded in the social and political practices that distinguish what is or is not science [45,49]. Boundary work can take a variety of foci, one of which is on objects [50] that blur the boundaries between science and policy.

Boundary objects, as originally defined [50], have three key characteristics:

1. They are material or abstract objects that simultaneously inhabit independent but intersecting social worlds;
2. They are flexible to the needs of multiple communities; and
3. And yet they are durable enough to maintain an identity.

By facilitating communication and interaction across boundaries between different groups of actors, boundary objects can serve as a focal point to co-produce actionable knowledge in inter- and transdisciplinary settings [51–53]. Novel concepts like 'resilience', 'ecosystem services', and 'sustainability' – all of which have interpretive flexibility but are meaningful in different groups - are commonly described as boundary objects [54–56]. Models [57,58] and participatory modeling processes [59] have also been acknowledged as boundary objects.

Boundary objects are useful as they integrate elements from scientific and political worlds to facilitate collaboration and exchange of multiple types of knowledge and action [53]. To the degree that they actually do this, they are important tools for co-production [25,47,60]. In our study, we found the concept of multi-hazard risk assessment, as well as the maps produced from the assessment, to be useful boundary objects that facilitated communication and coordination across disciplinary silos, between academic and municipal program staff, as well as between academic, city, and community group participants.

3. Multi-hazard risk assessment methodology

Academic and non-academic researchers as well as policy and program staff from the City of Austin combined inductive and deductive approaches to develop composite multi-hazard risk index for each census block group in the city. The approach included four primary steps: (1) assess the spatial sensitivity to hazards and differences across communities in their overall capacity to prepare for, respond to, and recover from hazards, using a quantitative social vulnerability index adapted from a well-vetted and often-used tool, the SoVI®; (2) assess the spatial exposure of three independent hazards—i.e., flooding (specifically, fluvial, or riverine, flooding), wildfire, urban heat; (3) conduct a single risk assessments combining sensitivity and exposure for each independent hazard; and (4) develop a composite multi-hazard risk index at census block group level.

3.1. Social vulnerability index

This study quantifies a social vulnerability index for the City of Austin at the census block group level adapting the SoVI® for the context in Austin. Austin is grouped into 640 Census Block Groups (CBGs) via the 2016 American Community Survey. The CBG scale is the lowest resolution of which census-based socioeconomic data exists in Austin. This scale is large enough to dampen outliers and potential errors in sociodemographic data, and yet small enough to capture variation in demographic makeup across the city.

Data for the index come from the U.S. Census 2013-17 American Community Survey (ACS). Of the total number of block groups in Austin (640), one (1) block group that correspond to Austin-Bergstrom International airport has been excluded from the data. From the 29 variables used for the SoVI® at the census tract level, 4 variables—i.e., Hospitals Per Capita, Percent of population without health insurance, Nursing Home Residents Per Capita, Percent Female Headed Households—were excluded due to their data availability at CBG level. Data for the remaining 25 variables was normalized using the min-max feature scaling method (see equation below).

$$X_{Normalized} = \frac{X_{original} - X_{\min}}{X_{\max} - X_{\min}}$$

The min-max method is a straightforward normalization technique common in social indicators research [61]. This assigns values for all variables scaling from 0 to 1, enabling the data to have comparable reference points. One disadvantage of using normalization, however, is that the final score is not an absolute measurement of social vulnerability for a single CBG location, but rather a relative value in which all CBG's in Austin can be compared. Utilizing such normalized values is useful for benchmarking progress in reducing vulnerability and enhancing resilience over time and across space.

With the normalized dataset, a principal component analysis (PCA) with varimax rotation was performed to reduce the dimensionality of a data set with statistically optimized components [62]. The variables are evaluated based on eigenvalue (>1.0), variance explained by each component, loading score for each factor (>| 0.50), and meaningfulness of each component. The process of calculating the Social Vulnerability Index score is summarized in Fig. 1. To avoid confusion with the established Centers for Disease Control SVI [39] or SoVI® [34] we will refer to our index as ATXSVI.

As a result of principal component analysis, 7 variables were eliminated leaving eighteen (18) variables remaining to construct the social vulnerability index (Table 1) at the CBG. Summarized in Table 1, six components were identified (i.e., Wealth, Language and Education, Elderly, Housing Status, Social Status, and Gender), explaining 74.48% of the total variance.

Finally, the orientation of each component was adjusted so that the directionality of the factor effect corresponds theoretically to higher social vulnerability (indicated on Cardinality column in Table 3). Positive component direction is associated with increasing vulnerability, while negative component direction is associated with decreasing vulnerability. Normalized and direction-adjusted values of each variable were summed together to determine the numerical composite social vulnerability score for each CBG.

3.2. Single hazard exposure assessment

3.2.1. Flood exposure

The flood exposure scores are developed based on the Creek Flooding Problem Score values developed by the Watershed Protection Department of the City of Austin [63]. The Problem Score accounts for public safety and property protection concerns for structures and low-water crossings using modeled flood depths for 2-, 10-, 25-, and 100-year storm events. The deeper and more frequent the predicted flooding, the higher the score, indicating higher probability of being exposed to the creek flooding and property damage. Numeric problem severity scores are calculated for each property based on resource values (see Table 2) and modeled flood frequency and depth. The flooding threat to a property i (FTi) is calculated as Equation (1), representing a "Raw" flood score for each property [63].

$$FT_i = RV_i{}^* \left(\frac{1}{2}D_2 + \frac{1}{10}D_{10} + \frac{1}{25}D_{25} + \frac{1}{100}D_{100}\right) \quad (1)$$

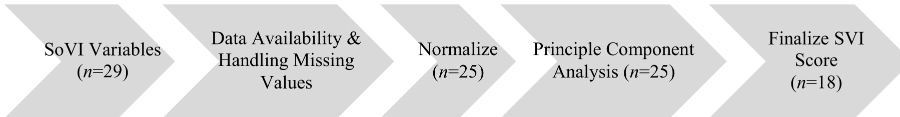

Fig. 1. Process of ATXSVI score calculation.

Table 1
Principal component analysis summary (variance) at block group level.

Variable		Loading Scores	Component	Cardinality	Variance Explained (%)
1	QRICH	0.915	Wealth	(−)	17.53
2	MDHSEVAL	0.892			
3	PERCAP	0.86			
4	MDGRENT	0.61			
5	QESL	0.806	Language & Education	(+)	14.51
6	QSPANISH	0.739			
7	QED12LES	0.732			
8	QSSBEN	0.896	Elderly	(+)	12.17
9	QAGEDEP	0.859			
10	MEDAGE	0.658			
11	PPUNIT	0.874	Housing Status	(+)	11.91
12	QFAM	0.844			
13	QCVLUN	0.723	Social Status	(+)	9.61
14	QBLACK	0.666			
15	QNOAUTO	0.559			
16	QPOVTY	0.533			
17	QFEMALE	0.877	Gender	(+)	8.75
18	QFEMLBR	0.836			
			Total Variance Explained		**74.48**

Table 2
Resource values for each type of resource.

Resource Type	Resource Value (RV)	Resource Type	Resource Value (RV)
Public Care Facilities	100	Residential: Single Family	60
Residential: Multifamily	80	Non-Residential	60
Mixed Use	80	Parking Garage	40

RV_i indicates the resource value for property i and D_2, D_{10}, D_{25}, D_{100} indicate the depth of flooding (ft) at the 2-, 10-, 25-, 100-year storm interval, respectively.

Adapted from "Watershed Protection Master Plan" by City of Austin Watershed Protection Department.

These raw scores are normalized to range from 0 to 100, where a score of 0 reflects ideal watershed conditions and a score of 100 represents the highest (worst) problematic score. Since the structural flooding mostly occurs within a flood plain [63], the proportion of the floodplain area within the block group was multiplied as a weight value (w_j) for the CBG (Equation (2)).

$$w_j = \frac{\textit{Area of floodplain within the block group } j}{\textit{Total Area of the block group } j} \quad (2)$$

Based on the flood problem scores for properties and the weight value, the creek flooding exposure scores for CBGs are calculated by summing all individual scores of properties within the block group (Equation (3)) and normalized to range from 0 to 1.

$$\textit{Flood Exposure Score for census Block Group } j = \sum i \in P(j) FT_i {}^* w_j \quad (3)$$

P(j) represents the set of all properties within the census block group j. Total number of 199 CBGs that do not contain floodplain have the weight value of 0.0, resulting the flood exposure score of 0.0. These CBGs were indicated as "Not in floodplain" on the map.

3.2.2. Wildfire exposure

The wildfire exposure scores are developed based on the Wildfire Risk scores calculated for the Austin-Travis County Community Wildfire Protection Plan (CWPP) in 2014 [64]. The CWPP defined wildfire risk as the product of "*the probability of a wildfire under conditions conducive to large, fast-moving fires that burn through fuels producing high heat energy and flaming embers and the negative consequences associated with the events.*" The scores are calculated based on two factors, spot risk and structure combustion risk.

The first factor, spot risk, is defined as the probability that spot fire ignition would occur due to embers. The risk associated with spot fires are assessed using the burn probability and spotting distance, which are outcome parameters from the wildfire behavior modeling software, FlamMap [65]. The burn probability estimates the likelihood that a pixel will burn given a random ignition, and it is calculated by "number of fires per pixel" divided by the "maximum number of fires per pixel". The spotting distance represents the behavior of fire that naturally transported embers causing new fire outside of main fire perimeter [66,67].

The second factor, structure combustion risk, is defined as the probability of structure loss during a wildfire and calculated as burn

Table 3
Descriptive statistics for each hazard and risk score.

		Min	Max	Mean	Median	# of Null Values	Null Desclription
Sensitivity (ATXSVI only)	Raw	0.004	0.263	0.124	0.119	1	Airport
	Normalized	0.000	1.000	0.462	0.444	1	Airport
Exposure (Flood Only)	Raw	0.000	0.948	0.114	0.080	199	Not in Floodplain
	Normalized	0.000	1.000	0.121	0.085	199	Not in Floodplain
Flood Risk (ATXSVI + Exposure)	Raw	0.000	1.738	0.179	0.122	200	Not in Floodplain + Airport
	Normalized	0.000	1.000	0.103	0.070	200	Not in Floodplain + Airport
Exposure (Wild Fire Only)	Raw	–	–	–	–	0	–
	Normalized	0.000	1.000	0.573	0.582	0	–
Wildfire Risk (ATXSVI + Exposure)	Raw	0.000	1.619	0.837	0.841	1	Airport
	Normalized	0.000	1.000	0.517	0.519	1	Airport
Exposure (Heat Only)	Raw	0.021	0.999	0.502	0.492	1	Airport
	Normalized	0.000	1.000	0.491	0.481	1	Airport
Urban Heat Risk (ATXSVI + Exposure)	Raw	0.000	1.685	0.729	0.720	1	Airport
	Normalized	0.000	1.000	0.433	0.427	1	Airport
Multi-hazard risk index	Raw	0.444	2.104	0.972	0.946	1	Airport
	Normalized	0.000	1.000	0.318	0.303	1	Airport

probability multiplied by fire line intensity. The fire line intensity, which is also one of the outputs of the FlamMap, indicates the rate of heat release along the fire front.

The wildfire scores from the CWPP are calculated for over 300,000 parcels, with the 30-m spatial resolution (raster). In order to match the resolution of this study, the wildfire exposure score was aggregated and averaged into the CBGs (polygon), and normalized using the GIS software, QGIS.

3.2.3. Heat exposure

The urban heat island effect, in which temperatures are higher in urban compared with surrounding rural environments, presents a significant climate-related hazard. Urban heat, and extreme variations in local air temperatures, are a key metric for public health outcomes [68]. A variety of methods are utilized to index urban heat, many of which include specialized temperature sensors not currently available for this study. Many studies focus on either impervious surfaces, which absorb and retain heat, or greenspaces and tree cover that have a cooling effect, or a combination of both [69].

This study used the Urban Imperviousness and Tree Canopy layers of the 2016 National Land Cover Database, the fifth generation of a 30-m resolution, spatially explicit land cover dataset covering the continental United States (Yang et al., 2018). Since heat generates a variety of impacts across time and space, assessing the relative impacts of Imperviousness and Tree Canopy involves prioritization about different heat risk phenomena. Tree Canopy provides invaluable shade during the day, while Imperviousness has a greater impact on night-time temperatures. Both factors are significant, so this research assumes an equal weight for both to be inclusive of night- and day-time heat risk (Equation (4)).

$$\textit{Heat Exposure Score for Census Block Group } j = 0.5\ IMP_j + 0.5^*\left(1 - TC_j\right) \tag{4}$$

IMP_j and TCj indicate the average percentage of impervious cover and average percentage of tree canopy of census block group *j*, respectively. Since the two variables have inverse directionality (high tree canopy correlates to low risk, and vice versa for imperviousness), TCj is subtracted from 1.

3.3. Multi-hazard risk assessment

The multi-hazard risk index is computed by first computing a risk index for each individual hazard (*HRI*), in this study, combines the exposure score (section 3.2.1 - 3.2.3) and sensitivity score (section 3.1) for all CBGs. These scores are calculated for all census block groups in the City of Austin. As shown in Equations (5)–(7), the risk score for each hazard was calculated as sensitivity score (ATXSVI score normalized into the range from 1 to 2) multiplied by the corresponding exposure score (normalized into the range from 0 to 1).

$$HRI_F(j) = SVI_j{}^*\textit{Flood Exposure Scorefor block group } j \tag{5}$$

$$HRI_{WF}(j) = SVI_j{}^*\textit{Wildfire Exposure Scorefor block group } j \tag{6}$$

$$HRI_{UH}(j) = SVI_j{}^*\textit{Urban Heat Exposure Score for block group } j \tag{7}$$

In order to develop a composite index assessing the risk from multiple hazards, we developed a composite multi-hazard risk index (*MHRI*) for all CBGs in the City of Austin. The composite score for block group *j*, $MHR\ I_{Composite}(j)$, is calculated as follows:

$$MHRI_{Composite(j)} = w_F{}^*HRI_F(j) + w_{WF}{}^*HRI_{WF}(j) + w_{UH}{}^*HRI_{UH}(j)$$

The w_F, w_{WF} , and w_{UH} indicate weight factors for each shock/stressor, which were all assumed to be 1, representing the equal importance across the three.

4. Results

Figs. 2–4 and Table 3 report the results of the multi-hazard risk assessment depicting social vulnerability, single hazard exposure, and the composite multi-hazard risk score.

4.1. Social vulnerability index

The normalized ATXSVI score ranges between 0 and 1 with mean value of 0.462. The ATXSVI score of 0.0 indicates the least vulnerable (blue in the figures), and 1.0 indicates the most vulnerable (red in the figures). Notably, the CBG for Austin-Bergstrom Airport has a "null value" equal to zero that is evident in southeast Austin. Fig. 2a shows the distribution of raw social vulnerability scores and geospatial normalized scores mapped to CBGs in Austin (Fig. 2b).

4.2. Single hazard exposures

The flood exposure score ranges between 0.0 and 0.948 with mean value of 0.114 (median value of 0.08). The normalized flood exposure score ranges between 0 and 1 with mean value of 0.121. The score of 0.0 indicates the least exposure (blue in Fig. 3a), and 1.0 indicates the most exposure (red in Fig. 3a). The normalized wildfire exposure score ranges between 0 and 1 with mean value of 0.501. The score of 0.0 indicates the least exposure (blue in Fig. 3b), and 1.0 indicates the most exposure (red in Fig. 3b). The exposure score for urban heat ranges between 0.021 and 0.999 with mean value of 0.502. The normalized heat exposure score ranges between 0 and 1 with mean value of 0.491. The score of 0.0 indicates the least exposure (blue in Fig. 3c), and 1.0 indicates the most exposure (red in Fig. 3c).

4.3. Multi-hazard risk index

The composite multi-hazard risk index ranges between 0.444 and 2.104 with the mean value of 0.972 (median value of 0.946). The normalized climate hazard risk score ranges between 0 (least vulnerable; blue in Fig. 4) and 1 (most vulnerable; red in Fig. 4) with mean value of 0.318. Table 3 presents descriptive statistics for all calculations.

The resulting multi-hazard index show that no census block groups are hazard risk free (Table 3), although there are clear spatial patterns of CBGs with higher multi-hazard risk located in central east and southeast Austin (Fig. 4).

5. Discussion

The spatial mapping of sensitivity (social vulnerability), single hazard exposures, and multi-hazard risk indices is a powerful tool for building urban community resilience and directing future research and community engagement efforts. The research not only presented a novel analytical approach for thinking about multi-hazard risks by incorporating social vulnerability, but in doing so it connects hazard science to climate adaptation and disaster risk reduction efforts – a communication and collaboration gap that needs to be addressed [13]. When viewed

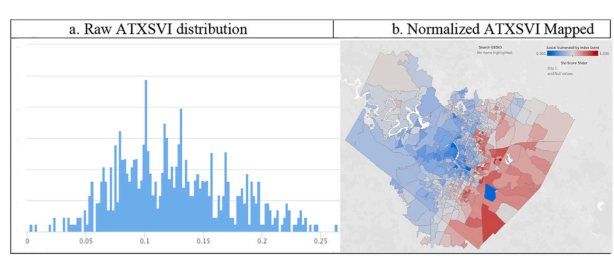

Fig. 2. Social Vulnerability by Census Block group in Austin. Figure 2a. Raw ATXSVI distribution Figure 2b. Normalized ATXSVI Mapped.

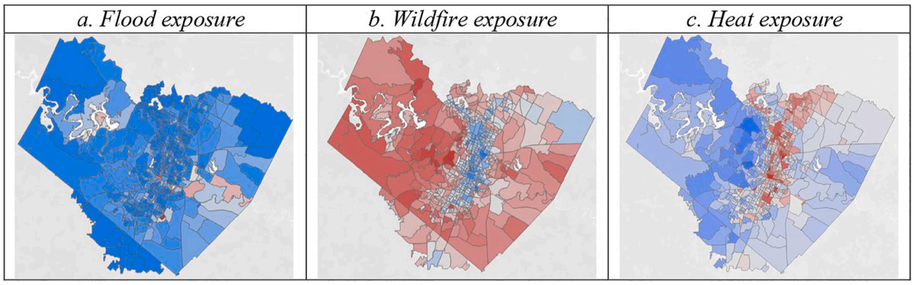

Fig. 3. Single Hazard Exposures in Austin. *3a. Flood exposure 3b. Wildfire exposure 3c. Heat exposure.*

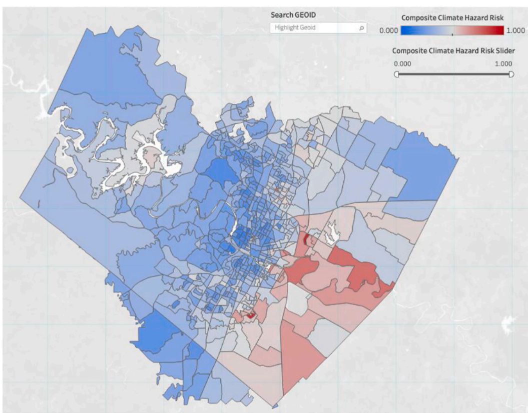

Fig. 4. Austin Multi-hazard Risk (flood + wildfire + heat + social vulnerability).

singularly, the social vulnerability index map (Fig. 2) and hazard exposure maps (Fig. 3) reaffirm city and nonprofit agency assumptions about vulnerable communities and areas of high hazard exposure.

When combined, city program staff and nonprofits have a more holistic view from which to understand vulnerability and strategies to build community resilience. Most neighborhoods possess some form of hazard risk with heat occurring within the urban core, fire along the peri-urban fringe, and flooding along riparian corridors. However, only a few neighborhoods have multiple or cascading risks in addition to relatively high social vulnerability. These are scattered across the Eastern Crescent, allowing for a geographically distributed yet targeted approach to community engagement.

When considering community vulnerability as a function of hazard exposure, sensitivity, and adaptive capacity [19], the multi-hazard assessment provides information regarding three policy intervention leverage points [32,70]. First, policy can target the reduction of exposure to hazards. In addition to investments in traditional infrastructure, nature-based infrastructure solutions have multiple benefits with broad climate adaptation and hazard risk reduction capabilities [71–73]. Second, reducing sensitivity means addressing the social factors that make residents more sensitive to the impacts of a hazard event. Transportation infrastructure, health and social policies, and housing policies that prevent displacement of long-time residents are various policy levers that can decrease social vulnerability over time. Much like the mapping of multiple hazards, policy to address these issues comes from multiple municipal departments that are frequently siloed and fragmented with regards to disaster risk reduction [74]. Third, and not accounted for in our multi-hazard risk assessment methodology, policy-makers and practitioners need to build adaptive capacity across multiple scales from individuals and households to inter-organizational networks and municipal and regional institutions [75–77]. Policies and programs that build adaptive capacity, for example by strengthening social bonds in neighborhoods [78], can increase adaptive behavior to hazards.

In addition to the policy relevant information provided by the multi-hazard risk, we found the concept of "multi-hazard assessment" and the actual maps themselves performed as effective boundary objects [79] and served as a tool to kickstart hazard and risk reduction co-production between researchers, city officials, nonprofits, and community members. The goal-oriented and context-based nature of this project were key conditions [47] that catalyzed numerous transdisciplinary joint research and community engagement projects that are ongoing (as of September 2021). For example, the multi-hazard assessment revealed combined hazards disproportionately impacting certain census block groups in southeast and north central Austin. Using this "object" as a starting point, a team academics-city staff-community groups led a proposal to the National Oceanic and Atmospheric Administration (NOAA) that was subsequently funded. The academic/non-academic group used the maps to determine the boundary of the campaign and particular communities they proposed to engage with throughout the research process. This spin-off project is working directly with community groups to assist with data collection and co-designing solutions, similar to efforts in Portland, Oregon and other places [80] These are the "boundary object" seeds of functional and transformative co-production.

The promise of co-production reordering the science-society relationship [60] rest in an explicit acknowledgement of multiple ways of knowing and doing and an addressing power and governance structures to empower relatively marginalized actors and build community resilience in vulnerable communities [25,81]. Municipalities can no longer rely solely on traditional public participation processes and data from historic climactic events to determine future impacts from extreme weather. Rather, new ways are needed to engage communities and invest in housing, infrastructure (roads, bridges, trails, sidewalks), utilities (electrical water and stormwater), community facilities (libraries, recreation centers, health centers) and public open space such as parks, green belts and sports fields. Multi-hazard risk assessments provide information useful for identification of communities and neighborhoods to include in hazard risk reduction co-production.

6. Limitations and conclusion

Improved and refined technical modeling of hazards is of little use if not embedded in the policy, regulatory, institutional, and cultural factors that hazard mitigation and preparedness occurs. The framework provided here offers an approach to a multi-hazard assessment combined with social vulnerability for census block groups. The approach provides a justifiable and a meaningful measure of the relative risk and resilience and of the spatial variation of risk across Austin. Importantly, our approach is reproducible utilizing publicly available data for the social vulnerability index (American Community Survey, U.S. Census Bureau); urban heat exposure (National Land Cover Dataset); and utilizing open data from the City of Austin for flood and fire. The multi-hazard risk assessment process, and the products, were a boundary object that facilitated research and learning across traditional hazard science silos and sparked information exchange and engagement between researchers-program staff-and community groups.

There are a few limitations to note. First, we're suggesting this process was useful in initiating a hazards and risk reduction co-production process. Over time, how the effort becomes more pluralistic (or not), continues to interact and iterate, empowers relatively marginalized voices, and transforms traditional institutions will be the true measure of success for the assessment and maps as a boundary object. Second, estimating hazards at a census block group smooths over important variation of household exposure within neighborhoods. This decision was made by the data availability constraints to construct the social vulnerability index and the necessary alignment of spatial scales for combining the single hazard assessments and sensitivity scores. Other, more community engaged, practices of measuring social vulnerability exist [42–44]. Relatedly, there are multiple approaches to modeling hazard exposure – flooding is a good example. We worked with the Creek Flooding Problem Score as part of the academic/non-academic collaboration since this is the primary method the city utilizes to base mitigation and resource allocation decisions despite the method not accounting for pluvial and nuisance flooding. Moreover, social vulnerability conceptually addresses capacity to cope it is a questionable proxy for capacity to adapt. Social dimensions of adaptive capacity of any given household, such as cohesion and networks [78], will vary in ways that a neighborhood social vulnerability index will not capture.

Despite these limitation, academic and non-academic partners have been able to utilize this tool to identify specific neighborhoods with relative high degrees of exposure to one or multiple hazards, coupled with relatively high social vulnerability. These neighborhoods can become leverage points where city policy, nonprofit programs, and public-private partnership investment can work to decrease exposure and/or increase adaptive capacity.

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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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