ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Multi-hazard risk in socially vulnerable communities across the United States

To cite this article: Leslie Sanchez *et al* 2025 *Environ. Res. Lett.* **20** 024008

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
6 August 2024

REVISED
25 November 2024

ACCEPTED FOR PUBLICATION
13 December 2024

PUBLISHED
10 January 2025

LETTER

Multi-hazard risk in socially vulnerable communities across the United States

Leslie Sanchez[1,*], Paul R Armsworth[2], Jasmine E Bruno[3], Sebastian Espinoza[2], Kathleen Galvin[4], Varsha Vijay[5] and Travis Warziniack[1]

1 Rocky Mountain Research Station, U.S. Forest Service, Fort Collins, CO, United States of America
2 Ecology & Evolutionary Biology, University of Tennessee, Knoxville, TN, United States of America
3 Foundation for Food & Agriculture Research (FFAR), Washington, DC, United States of America
4 Department of Anthropology, Colorado State University, Fort Collins, CO, United States of America
5 Science Based Targets Network, New York, NY, United States of America
* Author to whom any correspondence should be addressed.

E-mail: leslie.sanchez@usda.gov

Keywords: environmental justice, social vulnerability, multi-hazard risk

Supplementary material for this article is available online

Abstract

Society's most vulnerable communities bear the burdens of a multitude of environmental shocks and stressors, which are increasingly likely to occur simultaneously or in quick succession. However, our understanding of where environmental risks accumulate across the United States and how determinants of multi-hazard risk vary within the country remains incomplete. This study offers a more comprehensive understanding of the national scope and underlying drivers of compounding environmental risks from five hazards (water shortage, air pollution, wildfire, flooding, and impaired water quality) in socially vulnerable communities in the contiguous United States. By pairing census tract-level Social Vulnerability Index data from the Centers for Disease Control with hazard exposure data, we find that over 11 percent of the population—37 million people—is at high risk from multiple hazards. We find that multi-hazard risk disproportionately accumulates in the most vulnerable communities and therefore constitutes an environmental injustice. Nationally, socioeconomically vulnerable populations (e.g., low-income households and those lacking health insurance) are inequitably exposed to multiple severe hazards. However, the specific combinations of demographic and environmental drivers of risk accumulation vary across regions. While the widespread nature of environmental risk accumulation indicates that reducing multi-hazard risk will likely require comprehensive rather than piecemeal approaches, results also highlight the need for context-specific interventions.

1. Introduction

Vulnerable communities across the United States are exposed to a multitude of environmental hazards, ranging from floods [1] and fires [2] to water shortages [3] and air and water pollution [4, 5]. With less capacity to cope, they tend to suffer more damage than their less vulnerable counterparts [6]. Vulnerability and exposure to a given hazard determine the degree of environmental risk, i.e., the potential for harm, that a community incurs [7]. The inequitable exposure of vulnerable communities to singular hazards is well documented [1–6]. Such inequities constitute environmental injustices [8], which large-scale environmental policies like the federal government's Justice40 Initiative [9] have sought to reduce. However, communities are often exposed to not one, but rather several hazards [10, 11]. Despite a growing federal policy focus on ameliorating the unjust distribution of environmental risk, our understanding of where risk from multiple hazards accumulates at a national scale, or of how underlying drivers of multi-hazard risk vary across the country, remains limited. This study examines the extent to which multi-hazard risk accrues in vulnerable communities across the contiguous US (CONUS) and characterizes the underlying drivers of vulnerability and hazard exposure in areas where risk accrues. Social vulnerability is a multidimensional construct that measures a population's sensitivity and capacity to cope with a hazard. It includes characteristics like race and ethnicity, socioeconomic status, age, and housing type, which interact to shape a population's hazard response [12]. Research on environmental risk elucidates the individual elements of social vulnerability that are disproportionately exposed to environmental harms. Poverty and rurality predict exposure to worse water shortages [3] and water quality [13]. Black, Hispanic, and Native American communities are systematically exposed to worse air [4] and drinking water quality [14] than white, non-minority communities. Exposure to air and water pollutants is linked to worse academic performance [15], higher rates of cancer and asthma [16], and worse overall long-term health [17]—all outcomes that further increase vulnerability and perpetuate risk.

The multiple dimensions of social vulnerability interact to shape a population's susceptibility to a set of hazards in different ways [12]. Social vulnerability indices, by aggregating individual variables, provide relative measures of communities' overall resilience and vulnerability [18]. However, the underlying drivers of social vulnerability often vary across geographies [3, 12, 19]. While policymakers in the US and worldwide increasingly rely on social vulnerability indices to identify communities in most need of aid, differences in the underlying drivers of vulnerability suggest that the types of assistance that communities need will vary across geographies and specific hazards.

The inequitable exposure of socially vulnerable groups to singular hazards nationwide [3, 13, 19] likely extends to multiple hazards as well. This is because the physical processes that cause individual hazards are often similar and compounding [20, 21]. A warming climate, for instance, increases the duration and severity of drought [22, 23], which raises wildfire risks [24]. Extreme rainfall and flood events are increasingly likely to follow fires due to the effects of the same warming trends that catalyzed drought [25]. As the scope, severity, and frequency of individual hazards increase with climate change, hazards are more likely to overlap [26, 27]. Recent studies examine the effects of cumulative hazards on economic sectors [28], infrastructure [29], and health outcomes [30], underscoring the growing costs of multi-hazard risk [31]. Environmental justice research calls attention to the high costs of cumulative environmental burdens borne by marginalized groups [32]. Many of these studies focus on relatively localized geographies, showing that vulnerable communities are frequently exposed to multiple hazards whose synergistic effects further worsen economic disparities and health outcomes [11, 33, 34]. Such studies provide the contextual detail necessary for formulating actionable interventions, and identifying and addressing environmental injustices at larger scales [35]. However, there remains a gap in research on where hazards intersect with one another and with social vulnerability nationwide.

The paucity of empirical research examining the relationship between multiple hazards and the multiple dimensions of social vulnerability at a national scale [10] undermines risk reduction efforts in several ways. First, environmental injustices occur in the absence of the 'fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies' [8]. Federal legislation like the Bipartisan Infrastructure Law and Inflation Reduction Act allocated billions of dollars to help communities address climate risks and prepare for extreme environmental hazards [36], while the Justice40 Initiative requires that 40 percent of the legislative benefits flow to disadvantaged communities [9]. Identifying disadvantaged groups who are systematically exposed to worse hazards is therefore imperative to ensuring that they benefit and that legislation remedies such injustices. Further, understanding where multi-hazard risk accrues can help maximize program impacts by directing resources to the highest-risk areas.

Second, we do not have a good understanding of how the different dimensions contributing to overall social vulnerability intersect with multiple hazards at a national scale. Untangling this relationship is essential for identifying the populations most at risk and developing strategies to mitigate their unique vulnerabilities, particularly as government agencies and nongovernmental organizations rely on collated vulnerability indices to inform response and recovery efforts. Many conservation efforts falter in the long term because they do not adequately consider local vulnerabilities [37, 38].

Third, decision-makers tend to give more weight to low-probability, high-consequence events, like floods and fires that fall outside of the norm. However, chronic stressors like air pollution and water shortages are often positively correlated with acute shocks like flooding [39] and wildfire [24], and also disproportionately impact vulnerable communities. While the marginal benefits of risk mitigation efforts can be maximized by targeting the most degraded and vulnerable areas, policy decisions that address some hazards but not others may be inefficient or overlook long-running environmental injustices [40]. This study seeks a comprehensive understanding of the scope and distribution of multi-hazard risk accumulation across the CONUS, as well as the extent to which environmental risks unjustly accumulate. We focus on a set of five environmental hazards—water shortages, wildfires, flooding, air pollution, and impaired water quality—that are increasing in frequency and severity with climate change and development patterns, have been linked to environmental injustices, and that can be addressed via policy and management decisions. We overlay spatial data on hazard exposure for CONUS census tracts with the Center for Disease Control's (CDC) 2020 Social Vulnerability Index (SVI) data, which we select as a generalized measure of vulnerability. SVI is constructed using 16 American Community Survey (ACS) indicators, which fall under four vulnerability themes. We map multi-hazard risk and assess whether it constitutes an environmental injustice by regressing (i) overall SVI scores, (ii) SVI themes, and (iii) 16 SVI variables on the cumulative number of severe hazards to which a census tract is exposed. Disaggregating SVI into its root components provides important insight into whether some community characteristics are more exposed than others to multiple hazards. Finally, we examine the distinct but interrelated determinants of social vulnerability and cumulative hazard exposure across eight US Department of Agriculture (USDA) Climate Hubs. Identifying the heterogeneous drivers of environmental risk accumulation can help guide efforts to ameliorate risk.

2. Methods

This study assesses multi-hazard risk—a function of vulnerability and exposure to a set of hazards—by overlaying geospatial data on five environmental hazards, as a measure of exposure, with the CDC's SVI data, as a measure of vulnerability [3, 7]. In doing so, it (i) identifies areas across the CONUS where multi-hazard risk accumulates; (ii) ascertains whether exposure to multiple hazards constitutes an environmental injustice; and (iii) characterizes the spatially heterogeneous environmental and social drivers of multi-hazard risk accumulation. The sample includes 82 622 CONUS census tracts.

Measuring Hazard Exposure. Natural hazards selected for this study include water shortage, air pollution, wildfire, flooding, and impaired water quality. While some geographies may be more prone to experiencing some of these hazards than others (figure SI 2), we selected them because their severity is often a function of management decisions, they can be addressed through nature-based management strategies, and they have the potential to impact human and environmental well-being. Hazard variables are constructed using time-series data, which are averaged to capture long-term trends associated with chronic or frequent exposure rather than relatively short-term anomalies. Hazards are assessed as both continuous and dichotomous variables. To construct dichotomous measures of 'severe' hazard exposure, we benchmark severe hazards as those exceeding safety thresholds established in federal guidelines or as defined in the literature. (table SI 1 contains additional detail on hazard data and variable construction.)

Water shortages occur when demand exceeds supply. Using data from Heidari *et al* [41], we assess water shortage as the million cubic meter per month (MCM/mo.) deficit between demand and renewable supply between 1985–2015 for shortages lasting at least 12 months and with a 50-year return period. Following Sanchez *et al* [3], census tracts in the >90th percentile for shortage volumes are considered to be in severe shortage, I_{Shortage_i}. Air pollution is assessed using 2000–2016 1 km × 1 km fine particulate matter ($PM_{2.5}$) data from Di *et al* [42]. Census tracts are considered to have severe air pollution, I_{Air_i}, if mean $PM_{2.5}$ exceeds the U.S. Environmental Protection Agency's 2012 standard of 12 μg m^{-3} [43].

We use 30 m × 30 m resolution U.S. Forest Service data on the risk to potential structures (RPS) to assess potential wildfire exposure [44]. We calculate the mean RPS for each census tract. Following Dillon *et al* [44], a census tract is exposed to severe wildfire, I_{Fire_i}, if its national percentile rank is above the 90th percentile. Flooding is assessed using Flood Factor Index data from Bates *et al* [45], which estimates an area's 30-year likelihood of flooding. Index scores range from 1–10, with a higher score indicating greater flood potential. Severe flooding, I_{Flood_i}, is defined by Bates *et al* [45] as a flood index value of >7.

Water quality is assessed using three water quality indicators: (i) nitrogen loading concentrations (N mg l^{-1}), (ii) Ephemeroptera, Trichoptera, and Plecoptera (EPT) Index score, and (iii) enterococci concentrations (CCE/100 ml). Data are available from the U.S. Geological Survey and U.S. Environmental Protection Agency's Water Quality Portal [46] for 2013–2019. Availability, however, varies across census tracts. We select these indicators because of their well-documented impacts on both ecosystem and human health [47, 48], and together they provide a CONUS-level snapshot of water quality impairments that potentially occur in both urban and rural settings and across climate zones. Given the data limitations, our measure of water quality data is collected at the county-level.

USDA considers an EPT Index score of <7 to be poor water quality [49]. Enterococci concentrations of CCE > 470 per 100 ml surpass EPA water quality standards [50]. While there is no set threshold for nitrogen concentrations, we consider concentrations >1.875 mg l^{-1} to be severe, as such concentrations cause eutrophication in freshwater [51]. Because any of these water quality impairments could negatively impact a population, and data coverage is inconsistent across the CONUS, we are interested in the severity of exposure to *any* of the three water quality indicators. Therefore, a census tract's water quality, I_{WQ_i}, is considered severely impaired if the census tract is located within a county where water quality surpasses contamination thresholds for any of the three water quality indicators [52]. We also construct a continuous measure of overall water quality by calculating the national percentile rank for each water quality variable and selecting the highest of the three percentile rank values (indicating worse water quality).

For each hazard, n, census tract, i, is assigned a value of 1 if the hazard is severe and a value of zero if it is not. Cumulative severe hazard exposure, Haz_i, is equal to the total number of severe hazards to which a census tract, i, is exposed:

$$\mathrm{Haz}_i^* = I_{\mathrm{Air}_i} + I_{\mathrm{WQ}_i} + I_{\mathrm{Flood}_i} + I_{\mathrm{Fire}_i} + I_{\mathrm{Shortage}_i}. \quad (1)$$

Measuring Vulnerability. We use the CDC's SVI to measure social vulnerability at the census tract level [53]. SVI data is available for the full sample of CONUS census tracts, has been validated for robustness, convergence, and construct validity, and is commonly used by federal agencies to identify communities most in need of assistance [54]. The CDC uses 16 ACS variables, which are grouped into four themes to construct SVI scores (table SI 2). ***Socioeconomic vulnerability*** (Theme 1) includes measures of (1) poverty, (2) housing cost burden; (3) unemployment, (4) no high school diploma, and (5) no health insurance. ***Household characteristics*** (Theme 2) includes populations (6) aged $\geqslant 65$, (7) aged $\leqslant 17$, (8) with a disability, (9) single-parent households, and (10) who speak English 'less than well'. ***Minority status*** (Theme 3) includes (11) populations identifying as non-white racial or ethnic minorities. ***Housing and transportation*** (Theme 4) includes households in (12) multi-unit buildings, (13) mobile homes, (14) crowded homes, (15) lacking vehicle access, and (16) populations in group quarters.

SVI, themes, and variables are measured as percentile ranks ranging from 0 to 1, with 1 being the most vulnerable. Values reflect a census tract's vulnerability relative to other CONUS census tracts. The CDC constructs SVI first by calculating a census tract's percentile rank for each of the 16 ACS variables. Percentile ranks for SVI themes are calculated by summing the percentile ranks of the individual variables that comprise them. Overall SVI is calculated as the percentile rank of the sum of the four SVI theme ranks. Following Sanchez *et al* [3], we define highly socially vulnerable census tracts as having SVI scores $> .66$. Summary statistics are reported in table SI 3.

2.1. Empirical design

Our analysis proceeds in three steps. First, a mapping exercise identifies high-risk census tracts, which are both highly socially vulnerable (SVI $> .66$) and exposed to multiple severe hazards. Overlaying vulnerability and severe hazard exposure data reveals the scope and spatial patterns of risk accumulation across CONUS. Next, we examine the extent to which multi-hazard exposure constitutes an environmental injustice. If vulnerable groups are systematically exposed to more severe hazards, then we can conclude that multi-hazard risk is an environmental injustice. We use a Poisson regression, which accounts for the count nature of the dependent variable, to test the hypothesis that the number of severe hazards to which census tract, i, is exposed increases with social vulnerability:

$$\log\left(\mathrm{Haz}_i^*\right) = \beta_0 + \beta_1 SVI_i + \gamma_{\mathrm{state}}. \quad (2)$$

Here, Haz_i^* is the estimated mean number of severe hazards to which a census tract is exposed. Social vulnerability, SVI_i, is assessed differently in three separate regressions: one where SVI_i represents a census tract's overall SVI score; a second where SVI_i is a vector of the four SVI themes; and a third where SVI_i is a vector of the 16 ACS variables. Decomposing SVI into its root components enables us to identify the underlying drivers of vulnerability and to better understand the characteristics that an overall measure of SVI captures and/or potentially masks. Additional models control for agricultural and forested land use [55] and whether a census tract is located in an 'urban' county [56], as these factors may influence vulnerability and/or environmental quality (table SI 1). All models include state fixed effects, γ_{state}, to account for differences in state policies, enforcement, and budgeting. Standard errors are clustered at the county-level to account for potential spatial autocorrelation. We use variance inflation factors (VIF) to test for multicollinearity between ACS variables and between SVI themes [57]. All VIF values fell below a conservative threshold of 5, indicating a low risk of multicollinearity (tables SI 6 and SI 7).

Logit models act as robustness checks. Binary dependent variables are the estimated probabilities, $\Pr(\mathrm{Haz}_i^* = n)$, of exposure to n relative to zero hazards, where n has a value of 1, 2, or $\geqslant$3 severe hazards:

$$\Pr\left(\mathrm{Haz}_i^* = n\right) = \beta_0 + \beta_1 \mathrm{SVI}_i + \gamma_{\mathrm{state}}. \quad (3)$$

Finally, principal components analysis (PCA) identifies distinct but interrelated risk determinants underlying collated measures of social vulnerability and hazard accumulation in eight USDA Climate Hubs (figure SI 1). We conduct PCA for Climate Hubs because (i) different combinations of environmental hazards and demographic characteristics impact communities' resilience to a hazard in different ways, (ii) these factors are spatially heterogeneous, (iii) context-specific risk reduction strategies require a nuanced understanding of risk determinants, and (iv) Climate Hubs provide an institutional framework for delivering science-based information on climate impacts and vulnerabilities to relevant parties.

By Climate Hub, PCA are performed for 16 SVI variables within census tracts that are exposed to more than one severe hazard, and for the 5 hazards within highly socially vulnerable census tracts (SVI > .66). SVI variables and hazards are assessed as continuous variables. Components are unrotated, as the intent is to understand which variables best explain collated measures of social vulnerability and cumulative hazard exposure in potentially high-risk areas. First and second PC are reported for all models.

3. Results

3.1. Multi-hazard risk accumulation

Combining the CDC's SVI data with census tract-level data on exposure to flooding, wildfire, water shortage, air pollution, and water quality reveals the scope of the challenge that multi-hazard risk poses on a national scale. Figure 1 overlays highly socially vulnerable census tracts with the number of cumulative severe hazards to which they are exposed. Eleven percent of the CONUS population—37 million people—are both highly socially vulnerable and exposed to multiple ($\geqslant$2) severe hazards.

Risk accumulates along a U-shaped band that extends down the West Coast and across the southern section of the country, with California and the Southeast seeing the largest populations at high risk from multiple severe hazards (table SI 4). One-quarter to one-half of highly vulnerable populations in the Southwest and Southern Plains and nearly half of highly vulnerable Californians are exposed to at least one severe hazard. The share of the vulnerable population exposed to $\geqslant$2 hazards across the CONUS is almost double that exposed to zero hazards, indicating that multi-hazard risk is more likely than not to accumulate in communities with the least capacity to cope. Notably, no census tract is exposed to the full set of five severe hazards. This is because the unique combination of severe air pollution, flood, wildfire, and water shortage does not occur, and therefore cannot overlap with the fifth hazard, water quality.

3.2. Multi-hazard injustice modeling

Regression results depicted in figure 2 affirm that the number of severe hazards to which a census tract is exposed is increasing with its overall SVI score. On average, the expected number of severe hazards to which a census tract is exposed increases by .08–.14 for each one-unit increase in its SVI score. This equates to a 7–12 percent increase from the CONUS-level mean exposure to 1.2 severe hazards. The accumulation of multi-hazard risk therefore constitutes an environmental injustice, as vulnerable groups are systematically exposed to more severe hazards than their less vulnerable counterparts.

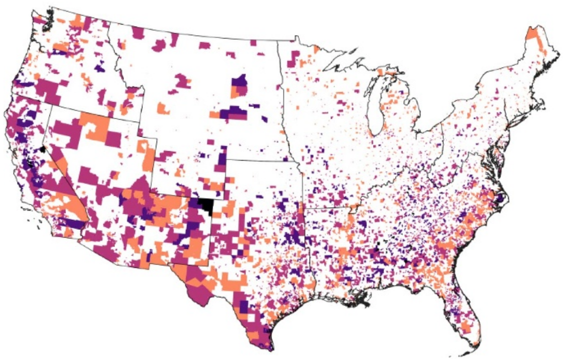
Deconstructing SVI into its four core themes reveals that the positive correlation between overall SVI and multi-hazard exposure is largely driven by socioeconomic vulnerability. On average, census tracts are exposed to between .25 and .30 additional severe hazards for each one unit increase socioeconomic vulnerability, which is largely a function of poverty and lack of health insurance (tables SI 9 and SI 10).

Logistic models comparing census tracts with exposure to 1, 2, and $\geqslant$3 severe hazards to those exposed to zero severe hazards show that the positive relationship between hazard exposure and SVI is most pronounced for those exposed to 2 hazards. Each one-unit increase in socioeconomic vulnerability is correlated with an average .10, .23, and .20 percentage point increase in the predicted probability of exposure to 1, 2, and $\geqslant$3 severe hazards, respectively. Coefficients on socioeconomic vulnerability in models assessing exposure to 2 and $\geqslant$3 hazards are twice that of models assessing exposure to one hazard, indicating that communities with the fewest resources are more likely to face not just one, but several hazards.

The negative relationship between minority status and severe hazard exposure is notable given the well-documented environmental injustices along the lines of race/ethnicity. While models that use the four SVI themes and 16 ACS variables as independent variables are robust to multicollinearity (tables SI 6 and SI 7), pairwise correlations between the 16 ACS variables help explain the negative relationship between minority status and cumulative hazard exposure (table SI 14). Positive, statistically significant correlations between minority status and housing burden, poverty, and lack of health insurance, which positively predict severe hazard exposure, indicate that the relationship between minority status and hazard exposure is not directly attributable to race/ethnicity. Rather, these other elements of social vulnerability are stratified along the dimensions of race/ethnicity.

3.3. Heterogeneous drivers of risk

Figure 3 overlays maps of each type of severe hazard in highly socially vulnerable census tracts to show the varying combinations of severe hazards that contribute to risk accumulation. High SVI scores tend to converge with worse flooding, water quality, and air pollution in the east, and with wildfire, water quality, and water shortage in the west. The on-the-ground impacts of different combinations of severe hazards on vulnerable communities will likely vary with hazard severity, duration, and with specific types



Key	Hazards	Pop.	Pop. (%)	Cum. (%)
	0	17,789,188	5.48	–
	1	55,837,537	17.61	–
	2	31,773,906	9.78	9.78
	3	4,764,875	1.47	11.25
	4	116,283	0.04	11.29

Notes: Highly socially vulnerable census tracts are those with SVI scores >.66. Population percentages are calculated as a share of the total CONUS population.

Figure 1. Severe hazard accumulation in highly socially vulnerable census tracts.

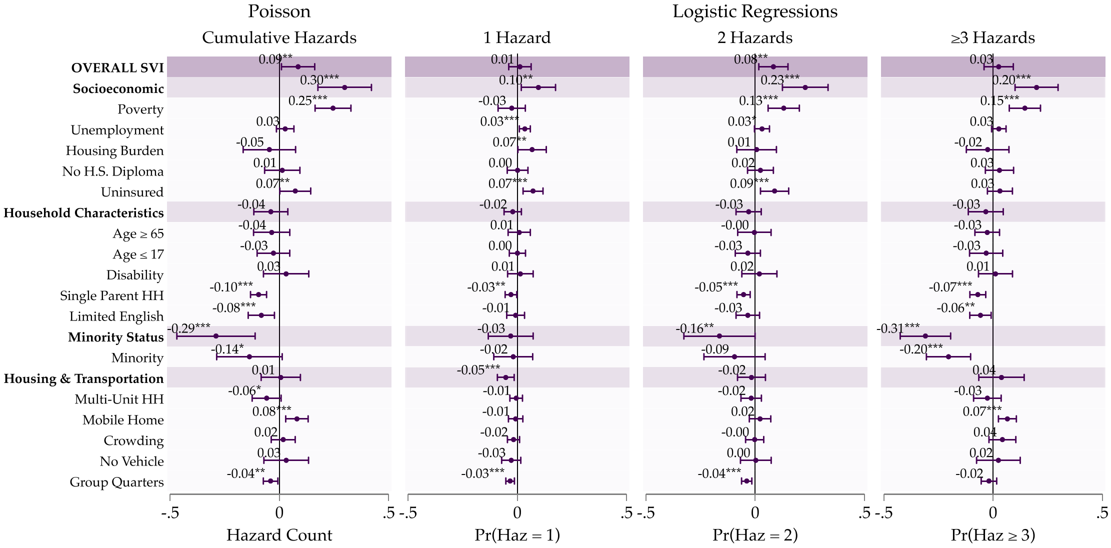


Figure 2. Average marginal effects of social vulnerability on severe hazard exposure. The figure presents estimates of the relationship between social vulnerability and severe hazard exposure, where social vulnerability, the independent variable, is assessed as (i) SVI (bold, capitalized), (ii) a vector of SVI themes (bold), and (iii) a vector of 16 ACS variables. Points represent estimated average marginal effect of social vulnerability on hazard exposure and bars are 95% confidence intervals. Poisson estimates are from tables SI 8, SI 9 and SI 10 (cols. 1). Estimates of the average marginal probability of exposure to 1, 2, or ⩾3 severe hazards are from tables SI 11, SI 12 and SI 13 (cols. 1, 3, and 5). $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

of vulnerabilities. Mapping compound risk, however, shows the particular combinations of hazards to which communities are exposed as well as the spatial distribution of compound risk.

Nationally, risks from water and air pollution are most pervasive, with 19 percent of the population in highly socially vulnerable areas exposed to severely impaired water quality, and 10 percent exposed to poor air quality (table SI 5). Severely impaired water quality, in combination with other hazards, threatens approximately 9 percent of the population, or 29 million people in highly socially vulnerable areas. Four percent of the population (13.5 million people) faces high risk from severe water and air pollution, while 17 percent of this group (2.7 million people) are exposed to an additional third or fourth severe hazard.

PCA identify the distinct and interactive drivers of risk accumulation across different parts of the US (here, based on USDA Climate Hubs). Rows 1 and 2 in figure 4 show PCA results for environmental hazards. Combinations of co-occurring hazards differ across Climate Hubs, but the relatively high eigenvectors on water shortage for PC 1 and 2 underscore the widespread role of water scarcity in risk accumulation.

Water shortage converges with other hazards under PC1 and PC2 to drive multi-hazard risk in all hubs except for the Southeast. It is worsening with wildfire and flooding in California, the Northeast, Pacific Northwest, Southern Plains, and Southwest. Hence, research showing that drier than normal conditions raise wildfire risk [24], and that major flood events are increasingly likely to follow a wildfire [25], appear to be playing out the the most socially vulnerable areas across the country. Worsening water shortages also converge with worse air pollution and water quality in the Midwest, Northern Plains, and

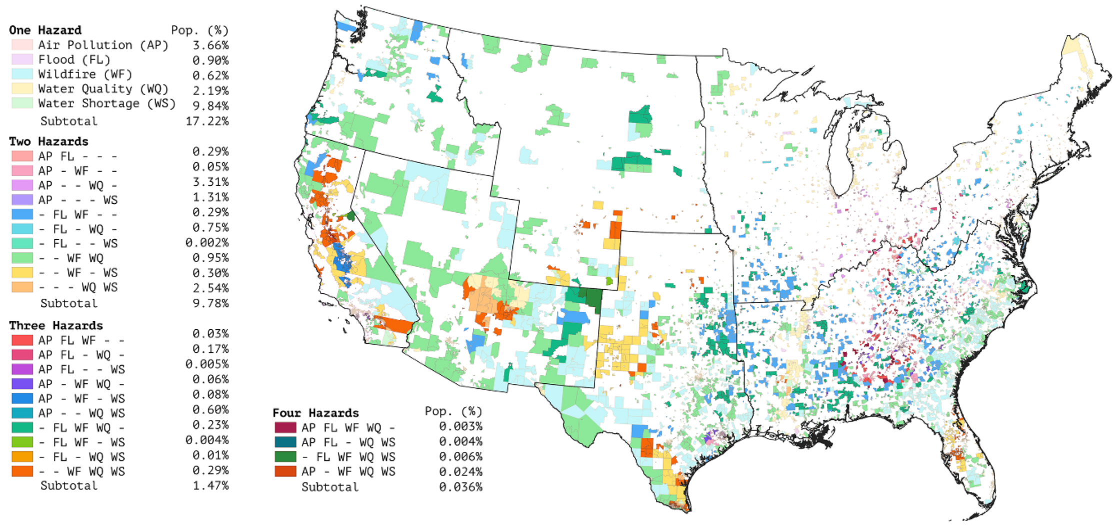


Figure 3. Combinations of severe hazards in highly socially vulnerable census tracts. Map shows the types and combinations of severe hazards to which highly socially vulnerable communities are exposed. The adjacent legend shows the combinations of overlapping hazards in highly socially vulnerable census tracts and the percentage of the CONUS population that is highly socially vulnerable and exposed to each combination of severe hazards. See table SI 5 for additional summary statistics on populations exposed to each set of severe hazards.

Southeast. Poor water quality can stem from air pollution (when particulate matter falls as precipitation) and water shortage (when water is insufficient to dilute contaminants). Air pollution can worsen when dry landscapes lack vegetation to tamp down dust and other airborne particulates.

Figure 4 (rows 3 and 4) graphs PCA results for SVI variables in census tracts exposed to >1 severe hazard. Socioeconomic factors—specifically poverty and lack of a high school diploma—drive vulnerability in high-risk areas across Climate Hubs. Combinations of socioeconomic vulnerabilities interact to varying degrees with household characteristics (e.g. age $\geqslant 65$, disability) and with different housing and transportation vulnerabilities (e.g. no vehicle, mobile home) under PC1.

While results further demonstrate that, nationally, the vulnerability component of multi-hazard risk stems from socioeconomic factors, they also reveal important regional differences in the nature of vulnerability. For instance, socioeconomic vulnerabilities in the Pacific Northwest under PC1 stem from poverty and housing costs, which worsen with multi-unit households. In other Climate Hubs, socioeconomic vulnerabilities stem from poverty and limited educational status and tend to worsen with mobile home residency. Socioeconomic vulnerabilities due to housing costs in the Pacific Northwest may require different adaptation strategies than in areas where lack of educational credentials, perhaps, limit earning potential. Likewise, mobile homes' physical vulnerability to various hazards differs from other housing types.

The prevalence of non-white minority populations with relatively high rankings under PC2 is a secondary driver of social vulnerability in all Climate Hubs. While socioeconomic factors contribute most to overall social vulnerability, structural inequities likely mean that minority populations are more likely to be socioeconomically vulnerable than their white, non-minority counterparts.

4. Discussion

Multi-hazard risk is pervasive across the CONUS, threatening over 10 percent of the population. Nearly 37 million people residing in highly vulnerable areas are exposed to multiple severe hazards. Given that hazards are increasing in severity and frequency with climate change, this number will likely increase without interventions. Moreover, socially vulnerable communities across the country are significantly more likely than their less vulnerable counterparts to be exposed to multiple severe hazards. The unjust accumulation of risk is especially pronounced in socioeconomically vulnerable and impoverished communities. However, social and environmental drivers of multi-hazard risk accumulation are spatially heterogeneous, as the combinations of severe hazards and vulnerability indicators that co-occur and worsen together in high-risk areas vary across Climate Hubs.

By mapping and analyzing the spatial overlap between concurrent hazard exposure and social vulnerability, our results affirm that single-hazard risk analyses underestimate risk for a large number of

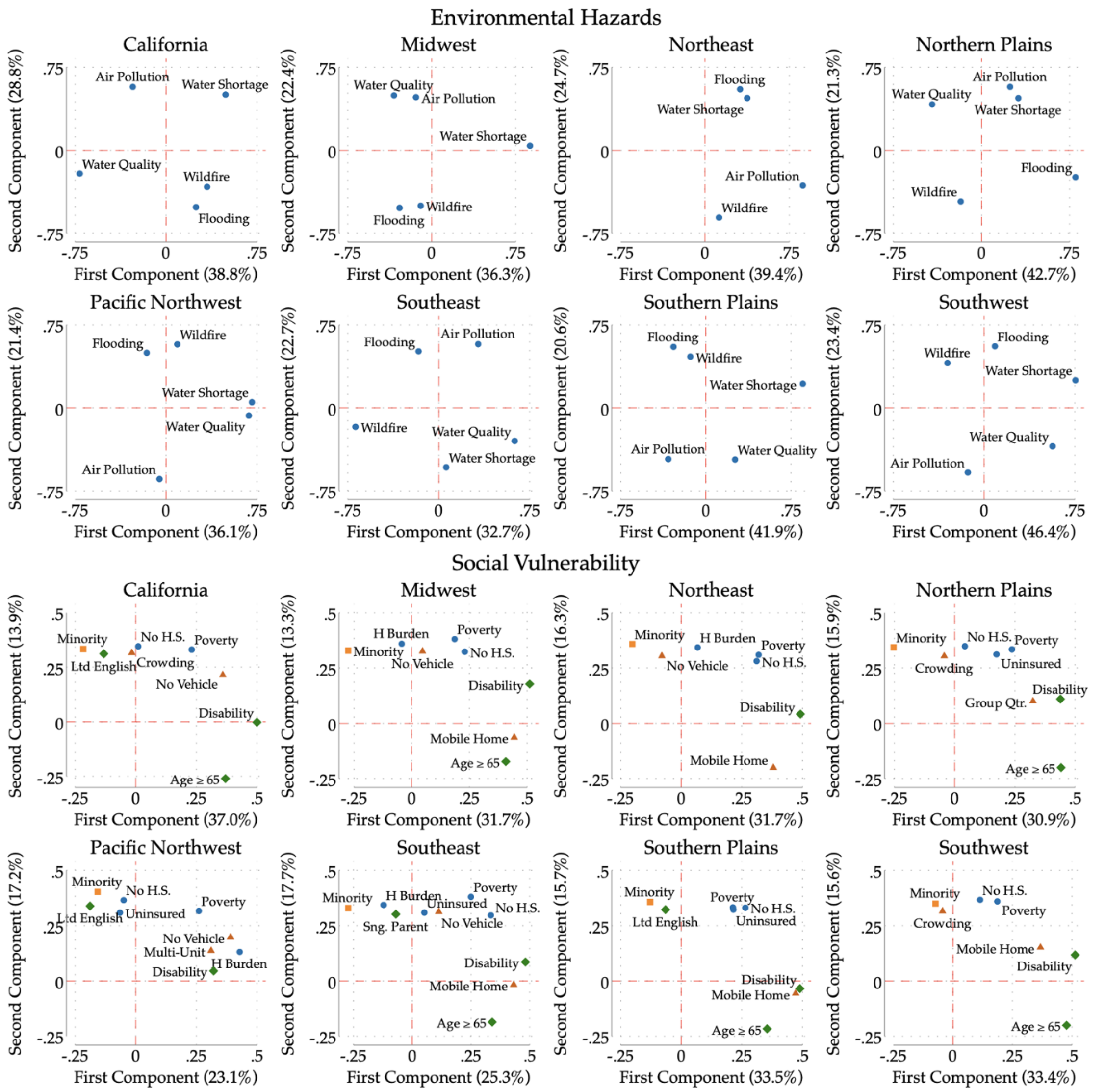


Figure 4. PCA results. The top two rows show factor loading plots for environmental hazards facing highly socially vulnerable census tracts with SVI scores > .66, by Climate Hub. All environmental hazards are assessed as continuous variables. Plots in the bottom two rows show SVI variables factor loading scores with values ⩾.3 for census tracts experiencing >1 severe hazard. The percentage of the variance explained by PC1 and PC2 are in parentheses on the *x* and *y* axes, respectively. Precise PC values are available in tables SI 15 and SI 16.

vulnerable communities. Piecemeal approaches to addressing single-hazard risks in these areas may be insufficient given the interrelated nature of hazards and feedback loops between hazards and vulnerability. Understanding the scope of the problem and identifying communities most in need of aid are critical first steps in risk mitigation. For instance, California and the Southeast emerge as areas where environmental risks compound in vulnerable communities. Relative to other regions, they have the largest shares and total populations residing in highly socially vulnerable census tracts that are exposed to ⩾2 severe hazards. Islands of inequality also emerge: census tracts in the Northern Plains with the greatest risk accumulation are on Native American reservations (figure SI 4), largely due to historic inequalities in environmental protections, political representation, and economic resources that tribes face.

By showing that socially vulnerable communities are inequitably exposed to more severe hazards, our results make clear that multi-hazard risk constitutes an environmental injustice. Of particular concern, this environmental injustice may worsen in the long term as climate change increases the likelihood that hazards occur simultaneously [58, 59]. Low-income and uninsured communities—two groups that are inequitably exposed to multiple hazards—expend larger shares of their resources to cope with rising economic costs of severe events [12, 31]. If forced to draw upon their already limited financial resources, they may fall further into poverty. With less access to health care, uninsured populations may suffer worse health outcomes [60, 61]. Positive feedback loops between hazard exposure and vulnerability likely mean that without interventions, the harm incurred by vulnerable communities will increase with each successive hazard.

Strategies to address risk might focus on either reducing vulnerability in high-exposure areas, reducing hazard exposure in high-vulnerability areas, or addressing both of these factors simultaneously. The prevalence of socioeconomic vulnerability as a widespread risk determinant and source of environmental injustice suggests that efforts to improve socioeconomic well-being could enhance resilience to environmental hazards at a national scale. However, variations in the underlying drivers of socioeconomic vulnerability likely mean that the same hazard or combination of hazards will have disparate effects across communities, thereby requiring interventions that are tailored to meet community needs. Introducing additional hazards or elements of vulnerability to the analysis would likely change the spatial distribution of risk accumulation as well as the impacts felt by communities, results underscore the need for comprehensive but nuanced initiatives to combat the compounding environmental risks in vulnerable communities.

Results also guide efforts for addressing hazard exposure. Conservation initiatives can maximize the impacts of individual projects by targeting areas where multiple hazards can be reduced by a single intervention. Several studies highlight the relationship between between agricultural water use and water shortages [62], and air [63] and water pollution [64]. If water shortages are raising the risk of wildfire, water quality, and/or air pollution, and agricultural land and water use contributes to water shortages, then adaptations in the agriculture sector could potentially ameliorate the risk from several interrelated hazards. Changes in forest management shown to reduce wildfire risk can also reduce exposure to flooding, and air and water pollution and may therefore have larger impacts in areas where multi-hazard risk accrues. Likewise, the band of high-risk census tracts across the southern half of the country highlights potential opportunities to link conservation projects where ecosystem services and/or management might mitigate hazards in these areas.

5. Conclusions

This study highlights the disproportionate concentration of environmental risks in socially vulnerable communities across the CONUS. Specifically, risk of environmental threats compounds in vulnerable communities more than they do in other communities. Increasing socioeconomic vulnerability of a community by one unit, on average, is correlated with a .23 percentage point increase in probability of exposure to two hazards and a .20 percentage point increase in probability of exposure to three hazards. Without proactive interventions, the challenges faced by these communities are likely to intensify over time.

Identifying areas where risks are most concentrated is essential to effectively allocate resources to communities who stand to benefit most from targeted support and intervention. Directing resources to areas where multiple risk factors intersect could help maximize the impact of risk reduction strategies. The extent of multi-hazard risk across the country underscores the urgent need for broad, coordinated risk reduction efforts. For example, the 2022 Inflation Reduction Act allocates 40 percent of the $500 billion in federal funding for clean energy initiatives to disadvantaged communities [65]. The resources made available through such initiatives provide critical support for communities grappling with a multitude of environmental hazards. More generally, addressing the root causes of vulnerability—such as poverty and lack of access to healthcare—in high-risk areas can enhance resilience and help reduce disparities. Effectively addressing multi-hazard risk, however, will likely require sustained efforts beyond what is currently in place. Importantly, the hazards and vulnerabilities facing individual communities are not uniform. The success of multi-hazard risk reduction initiatives is therefore likely to hinge on interventions that are tailored to communities' diverse needs and priorities.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Conflict of interest

This statement is to certify that all Authors have seen and approved the manuscript being submitted. We confirm that the article is the Authors' original work and that we have no conflicts of interest.

ORCID iDs

Leslie Sanchez https://orcid.org/0000-0002-0947-9535
Sebastian Espinoza https://orcid.org/0000-0002-4465-1222
Kathleen Galvin https://orcid.org/0000-0002-9003-8365
Varsha Vijay https://orcid.org/0000-0002-2665-7866

References

[1] Pallathadka A, Sauer J, Chang H and Grimm N B 2022 Urban flood risk and green infrastructure: who is exposed to risk and who benefits from investment? A case study of three U.S. cities *Landsc. Urban Plan.* **223** 104417
[2] Davies I P, Haugo R D, Robertson J C and Levin P S 2018 The unequal vulnerability of communities of color to wildfire *PLoS One* **13** 1–15
[3] Sanchez L, Warziniack T and Knowles M 2023 The inequitable exposure of socially vulnerable groups to water shortages across the United States *Environ. Res. Lett.* **18** 044022
[4] Hernandez D and Meng K C 2023 Do health disparities narrow with pollution disparities? Trends from California *American Economic Review, Papers and Proc.*
[5] Mueller J T and Gasteyer S 2021 The widespread and unjust drinking water and clean water crisis in the United States *Nat. Commun.* **12** 3544
[6] Blaikie P, Cannon T, Davis I and Wisner B 2004 *At Risk: Natural Hazards, People's Vulnerability and Disasters* 2nd edn (Routledge)
[7] IPCC 2014 *Climate Change 2014: Impacts, Adaptation and Vulnerability* (Cambridge University Press) p 1772
[8] U.S. Environmental Protection Agency 1998 *Technical Report* (U.S. Environmental Protection Agency)
[9] Executive Order 14008 2021 *Executive Order on Tackling the Climate Crisis at Home and Abroad* vol 86 FR p 7619
[10] Drakes O and Tate E 2022 Social vulnerability in a multi-hazard context: a systematic review *Environ. Res. Lett.* **17** 033001
[11] Chen C, Schwarz L, Rosenthal N, Marlier M E and Benmarhnia T 2024 Spatial heterogeneity in population health impacts and vulnerability to compound climate hazards: extreme heat and wildfire smoke in California *Sci. Adv.* **10** eadj7264
[12] Cutter S L and Finch C 2008 Temporal and spatial changes in social vulnerability to natural hazards *Proc. Natl Acad. Sci.* **105** 2301–6
[13] Levy Z, Jurgens B, Burow K R, Voss S, Faulkner K, Arroyo-Lopez J A and Fram M S 2021 Critical aquifer overdraft accelerates degradation of groundwater quality in California's Central Valley during drought *Geophys. Res. Lett.* **48** e2021GL094398
[14] McDonald Y J and Jones N E 2018 Drinking water violations and environmental justice in the United States, 2011–2015 *Am. J. Public Health* **108** 1401–7
[15] Stafford T M 2015 Indoor air quality and academic performance *J. Environ. Econ. Manage.* **70** 34–50
[16] Brender J D, Maantay J A and Chakraborty J 2011 Residential proximity to environmental hazards and adverse health outcomes *Am. J. Public Health* **101** S37–S52
[17] Zhang X, Chen Xi and Zhang X 2018 The impact of exposure to air pollution on cognitive performance *Proc. Natl Acad. Sci.* **115** 9193–7
[18] Cutter S L, Boruff B J and Shirley W L 2003 Social vulnerability to environmental hazards *Soc. Sci. Q.* **84** 242–61
[19] Wigtil G, Hammer R B, Kline J D, Mockrin M H, Stewart S I, Roper D and Radeloff V C 2016 Places where wildfire potential and social vulnerability coincide in the coterminous United States *Int. J. Wildland Fire* **25** 896–908
[20] Zscheischler J *et al* 2018 Future climate risk from compound events *Nat. Clim. Change* **8** 469–77
[21] De Angeli S, Malamud B D, Rossi L, Taylor F E, Trasforini E and Rudari R 2022 A multi-hazard framework for spatial-temporal impact analysis *Int. J. Disaster Risk Reduct.* **73** 102829
[22] Dai A 2011 Drought under global warming: a review *Wiley Interdiscip. Rev. Clim. Change* **2** 45–65
[23] Karl T R *et al* 2012 U.S. temperature and drought: recent anomalies and trends *EOS, Trans. Am. Geophys. Union* **93** 473–4
[24] Abatzoglou J T, Williams A P, Boschetti L, Zubkova M and Kolden C A 2018 Global patterns of interannual climate–fire relationships *Glob. Change Biol.* **24** 5164–75
[25] Touma D, Stevenson S, Swain D L, Singh D, Kalashnikov D A and Huang X 2022 Climate change increases risk of extreme rainfall following wildfire in the western United States *Sci. Adv.* **8** eabm0320
[26] Raymond C *et al* 2020 Understanding and managing connected extreme events *Nat. Clim. Change* **10** 611–21
[27] Kean J W and Staley D M 2021 Forecasting the frequency and magnitude of postfire debris flows across southern California *Earth's Future* **9** e2020EF001735
[28] Schlosser C A *et al* 2023 Assessing compounding risks across multiple systems and sectors: a socio-environmental systems risk-triage approach *Front. Clim.* **5** 1100600
[29] Barquet K, Englund M, Inga K, André K and Segnestam L 2024 Conceptualising multiple hazards and cascading effects on critical infrastructures *Disasters* **48** e12591
[30] Ebi K L, Vanos J, Baldwin J W, Bell J E, Hondula D M, Errett N A, Hayes K, Reid C E, Saha S and Spector J *et al* 2021 Extreme weather and climate change: population health and health system implications *Annu. Rev. Public Health* **42** 293–315
[31] Coronese M, Lamperti F, Keller K, Chiaromonte F and Roventini A 2019 Evidence for sharp increase in the economic damages of extreme natural disasters *Proc. Natl Acad. Sci.* **116** 21450–5
[32] Corburn J 2002 Environmental justice, local knowledge and risk: the discourse of a community-based cumulative exposure assessment *Environ. Manage.* **29** 451–66
[33] Su J G, Morello-Frosch R, Jesdale B M, Kyle A D, Shamasunder B and Jerrett M 2009 *An Index for Assessing Demographic Inequalities in Cumulative Environmental Hazards With Application to Los Angeles, California* (ACS Publications)
[34] Abel T D 2008 Skewed riskscapes and environmental injustice: a case study of metropolitan St. Louis *Environ. Manag.* **42** 232–48
[35] Cushing L, Faust J, August L M, Cendak R, Wieland W and Alexeeff G 2015 Racial/ethnic disparities in cumulative environmental health impacts in California: evidence from a statewide environmental justice screening tool (CalEnviroScreen 1.1) *Am. J. Public Health* **105** 2341–8
[36] Infrastructure Investment and Jobs Act 2021 *H.R.3684—117th Congress* (Congressional Record) (available at: www.congress.gov/bill/117th-congress/house-bill/3684)
[37] Catalano A S, Lyons-White J, Mills M M and Knight A T 2019 Learning from published project failures in conservation *Biol. Conserv.* **238** 108223
[38] Ford A T, Ali A H, Colla S R, Cooke S J, Lamb C T, Pittman J, Shiffman D S and Singh N J 2021 Understanding and avoiding misplaced efforts in conservation *FACETS* **6** 252–71
[39] Fan J, Rosenfeld D, Yang Y, Zhao C, Leung L R and Li Z 2015 Substantial contribution of anthropogenic air pollution to catastrophic floods in Southwest China *Geophys. Res. Lett.* **42** 6066–75
[40] Wibbenmeyer M, Anderson S E and Plantinga A J 2019 Salience and the government provision of public goods *Econ. Inq.* **57** 1547–67
[41] Heidari H, Arabi M and Warziniack T 2021 Vulnerability to water shortage under current and future water supply-demand conditions across U.S. river basins *Earth's Future* **9** e2021EF002278
[42] Di Q *et al* 2019 An ensemble-based model of $PM_{2.5}$ concentration across the contiguous United States with high spatiotemporal resolution *Environ. Int.* **130** 104909
[43] U.S. Environmental Protection Agency 2013 *National Ambient Air Quality Standards for Particulate Matter* (Federal Register, Vol. 78, No. 10)
[44] Dillon G K *et al* 2023 Wildfire risk to communities: spatial datasets of landscape-wide widlfire risk components for the USA *Fort Collins CO Forest Service Research Data Archive* vol 3 pp 159–1089

[45] Bates P D *et al* 2021 Combined modeling of US fluvial, pluvial and coastal flood hazard under current and future climates *Water Resour. Res.* **57** e2020WR028673
[46] Water Quality Portal 2021 *National Water Quality Monitoring Council, United States Geological Survey (USGS)* (Environmental Protection Agency (EPA)) (https://doi.org/10.5066/P9QRKUVJ)
[47] Dubrovsky N M *et al* 2010 The quality of our Nation's waters—nutrients in the Nation's streams and groundwater, 1992–2004 *US Geological Survey Circular* vol 1350 p 174
[48] Schwarzenbach R P, Egli T, Hofstetter T B, Von Gunten U and Wehrli B 2010 Global water pollution and human health *Annu. Rev. Environ. Resour.* **35** 109–36
[49] Bernard J M, Fripp J and Robinson K 2007 Stream restoration design handbook (210–VI–NEH) *National Engineering Handbook* (US Department of Agriculture, Natural Resources Conservation Service)
[50] US EPA 2012 *Recreational Water Quality Criteria* 820-f-12-058 (Office of Water, US Environmental Protection Agency Washington DC)
[51] Dodds W K and Smith V H 2016 Nitrogen, phosphorus and eutrophication in streams *Inland Waters* **6** 155–64
[52] U.S. Environmental Protection Agency 2021 *Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts* (EPA 430-R-21-003)
[53] CDC/ATSDR 2020 *CDC/ATSDR Social Vulnerability Index Database US* (Center for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program)
[54] Flanagan B, Hallisey E, Sharpe J D, Mertzlufft C E and Grossman M 2021 On the validity of validation: a commentary on Rufat, Tate, Emrich and Antolini's "How valid are social vulnerability models? *Ann. Am. Assoc. Geogr.* **111** 1131–53
[55] Dewitz J 2021 National landcover database (NLCD) 2019 products (Earth Resources Observation and Science (EROS) Center) (https://doi.org/10.5066/P9KZCM54)
[56] Ingram D D and Franco S J 2014 *2013 NCHS Urban-Rural Classification Scheme for Counties* vol 2014 (US Department of Health and Human Services, Centers for Disease Control and the National Center for Health Statistics)
[57] Thompson C G, Kim R S, Aloe A M and Becker B J 2017 Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results *Basic Appl. Soc. Psychol.* **39** 81–90
[58] de Ruiter M C, Couasnon A, van den Homberg M J C, Daniell J E, Gill J C and Ward P J 2020 Why we can no longer ignore consecutive disasters *Earth's Future* **8** e2019EF001425
[59] Gill J C and Malamud B D 2014 Reviewing and visualizing the interactions of natural hazards *Rev. Geophys.* **52** 680–722
[60] Benevolenza M A and DeRigne L 2019 The impact of climate change and natural disasters on vulnerable populations: a systematic review of literature *J. Hum. Behav. Soc. Environ.* **29** 266–81
[61] Apelberg B J, Buckley T J and White R H 2005 Socioeconomic and racial disparities in cancer risk from air toxics in Maryland *Environ. Health Perspect.* **113** 693–9
[62] Rosa L, Chiarelli D D, Rulli M C, Dell'Angelo J and D'Odorico P 2020 Global agricultural economic water scarcity *Sci. Adv.* **6** eaaz6031
[63] Abman R, Edwards E C and Hernandez-Cortes D 2023 Water, dust and environmental justice: the case of agricultural water diversions *Am. J. Agric. Econ.* 1–18
[64] Aillery M P, Gollehon N R, Johansson R C, Kaplan J D, Key N D and Ribaudo M 2005 Managing manure to improve air and water quality *Technical Report* (USDA Economic Research Service)
[65] Biden J 2021 Executive Order 13985: Executive Order on Advancing Racial Equity and Support for Underserved Communities Through the Federal Government *Federal Register* **vol 86** 7009–13