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RESEARCH ARTICLE

Disparities in self-reported extreme weather impacts by race, ethnicity, and income in the United States

Chad Zanocco[1]*, June Flora[1], Hilary Boudet[2]

1 Civil and Environmental Engineering, Stanford University, Stanford, California, United States of America, 2 School of Public Policy, Oregon State University, Corvallis, Oregon, United States of America

* czanocco@stanford.edu

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Abstract

Extreme weather events are expected to increase in frequency and severity due to climate change. However, we lack an understanding of how recent extreme weather events have impacted the U.S. population. We surveyed a representative sample of the U.S. public (n = 1071) in September 2021 about self-reported impacts they experienced from six types of extreme weather events within the past three years. We find that an overwhelming majority (86%) of the U.S. public reported being at least slightly impacted by an extreme weather event, and one-third (34%) reported being either very or extremely impacted by one or more types of extreme weather events. We clustered respondents into four impact groups, representing a composite of self-reported impacts from multiple types of extreme weather events. Respondents in the highest extreme weather impact group are more than 2.5 times as likely to identify as Black or Hispanic and 1.89 times more likely to live in a household with income levels below the Federal poverty level. We also observe reports of higher extreme weather impacts from respondents who are female, do not have a bachelor's degree and live in a rural area. Our results indicate that extreme weather impacts are being felt by a broad cross-section of the U.S. public, with the highest impacts being disproportionately reported by populations that have previously been found to be more vulnerable to natural disasters and other extreme events.

1. Introduction

The United Nations Secretary General described the recent IPCC Working Group report on climate change as a "code red" for humanity [1]. Moreover, the consequences of climate change are not equally distributed and are likely worsening global inequality [2–4], a trend that is expected to continue without comprehensive climate mitigation and adaptation policies. Such disparities can be observed through the differential impacts of extreme weather events, the frequency and severity of which—for certain events and under certain circumstances—can be linked to human caused climate change [5–7]. For example, at a global level, less developed countries are more likely to be impacted by increasingly frequent and intense heat waves due to climate change [8].

There are also notable heterogenous impacts among populations within countries. Such variation in population exposure and impacts is prominent in the United States [9], both for reasons related to geography but also due to existing social inequities, with certain populations (e.g., those living in poverty) being more vulnerable to the impacts of natural disasters [10].

The events themselves are not evenly distributed geographically. Certain extreme weather event types are more likely to occur within particular U.S. regions: hurricanes in the South and the East Coast, tornadoes in the Midwest, and wildfire in the West. Within and across these U.S. geographies, however, are differential climate-related impacts on populations, as well as a patchwork of climate adaptive policies applied at different levels of government [11].

An understanding of self-reported extreme events impacts at a population-level, therefore, is needed to characterize overall experiences of extreme weather across the U.S. public—and what members of society report being impacted the most. This is especially important given the constantly changing dynamics of extreme weather event impacts on U.S. populations and how these changing dynamics may intersect with impacts from other concurrent events, such as the COVID-19 pandemic [12]. Moreover, recent events may be impacting U.S. populations in ways that diverge from historical experiences with extreme weather—with 2021 alone including record-breaking wildfires [13], heat waves [14], winter storms [15], and hurricanes [16]—that left millions without power and water, sometimes for weeks at a time.

1.1 Experiences with extreme weather events

Extant research that has examined experience, exposure, and harm from extreme weather events have often focused on individual events (e.g., [17, 18]), events of the same type or in the same area (e.g., [19, 20]), or a collection of selected events with a similar magnitude of impacts on communities [21, 22]. Such approaches have yielded insights into the characteristics of those who are impacted by specific extreme event types and their harm from these events (e.g., [23, 24]). However, studies with national-level coverage of the U.S. general public's reported experiences with multiple extreme event types are less common (see [25] for an exception).

Recent polling in Fall 2021 found that approximately half (46%) of Americans reported first-hand experiences with extreme weather within the past 12 months and that two-thirds (67%) believed that extreme weather events were happening more often than in the past [26]. However, this polling effort did not measure the severity of impacts from extreme weather events and did not delineate experiences by different event types. To address this gap, we examine how experience with extreme weather has recently impacted the U.S. public across a range of event types and geographies, formalized in the following research questions:

RQ: What recent extreme weather events impacts are being self-reported by the U.S. public? How do these reported impacts vary by event type and geographic region?

These research questions, however, do not provide insight into how specific populations within the U.S. may be differentially impacted by extreme events, especially among those groups who have previously been found to be more impacted by natural disasters, extreme weather, and other disruptive events. Therefore, we also examine self-reported extreme weather impacts by sociodemographic characteristics identified in previous literature as being associated with higher levels of impact.

1.2 Differential experiences with extreme event impacts

Understanding the characteristics of those severely impacted by extreme weather is critical for planning, policy, and response efforts. Previous literature has established that certain populations can be more impacted by a variety of natural disasters and disruptive events, ranging from extreme weather events and environmental hazards to economic crises and pandemics [10, 27–29]. Using previous literature as a guide, we form a set of hypotheses with the overall objective of understanding disproportionate impacts from recent extreme weather reported by different populations in the United States. We focus on six interconnected sociodemographic characteristics that have been found in previous studies to relate to extreme event impacts: income (H1); race/ethnicity (H2 & H3); gender (H4); education (H5); age (H6); and rurality (H7).

Low income populations and those living in poverty have been found to be disproportionately impacted by natural hazards and disasters, both across the world and in the U.S. [30, 31]. Explanations for this relationship between poverty and more negative impacts from extreme events are multifaceted, ranging from the location of lower income housing in more disaster exposed areas [32, 33], to disproportionate losses in assets and well-being due to events [34], to less capacity to immediately respond to events and fully recover post-event [35]. There is also evidence that climate change impacts can increase future poverty rates [36]. Given this relationship between disasters and poverty, we form the following hypothesis:

H1. Respondents living in poverty will be more likely to report negative impacts from extreme weather events.

The COVID-19 pandemic has underscored how a disruptive event can also have differential impacts on racial/ethnic minority groups, particularly in the U.S. [37–39]. Indeed, previous research has found that other types of disruptive events, such as natural disasters and extreme weather events, can have differential impacts by race and ethnicity [40, 41]. For example, research has found that phenomena such as extreme heat exposure via heat island effects disproportionately impacts neighborhoods with high percentages of Latinos and African Americans [42–44]. Additionally, in disasters such as Hurricane Katrina, more than half of the fatalities were Black [45]. And, during the 2021 winter storm in Texas, it was historically marginalized minority neighborhoods that were the first to experience power outages [46, 47]. We therefore propose the following hypotheses:

H2. Respondents identifying as Black will be more likely to report negative impacts from extreme weather events.

H3. Respondents identifying as Hispanic will be more likely to report negative impacts from extreme weather events.

Research has also found that older adults are more likely to be impacted by disasters due to multiple factors, including a higher likelihood of chronic health conditions and sensory, cognitive, and mobility disabilities, as well as limited social and economic support systems [48, 49]. Evidence suggests that older adults have higher rates of mortality related to disasters [50], brought into sharp focus in the aftermath of California's 2018 Camp Fire where three-quarters of victims were age 65 years or older [51]. We therefore propose the following hypothesis:

H4. Older adults will be more likely to report negative impacts from extreme weather events.

Gender has long been linked to differential disaster impacts, with women having less access to resources such as health care and emergency housing following extreme weather events and disasters [52]. Women have also been shown to be less likely to receive economic assistance following disasters, making recovery from extreme events more challenging [53]. Additionally, there are indications that domestic violence may increase in the wake of nature disasters [54], and, at a global level, there is a gendered gap in life expectancy, with life expectancy of women lowered more compared to men following natural disasters [55]. Given this relationship between gender and differential impacts from extreme weather events and disasters, we form the following hypothesis.

H5. Females will be more likely to report negative impacts from extreme weather events.

Having lower levels of educational attainment has also been found to be associated with increased impacts from extreme events as it can make preparing for disasters, accessing resources, and seeking out information and assistance during and after the event more challenging [56]. In turn, having higher levels of educational attainment, both at the individual-level and across society, is related to better preparedness and responses to disasters, as well as less negative impacts from events [57–59]. Given this connection between educational attainment and vulnerability, we pose the following hypothesis:

H6. Respondents with lower educational attainment will be more likely to report negative impacts from extreme weather events.

Residents living in rural communities may be more vulnerable to disasters and extreme events due to lack of local government capacity, as well as often less availability of government funding for prevention and recovery compared to urban settings [60, 61]. Moreover, an analysis of rural communities found them to be more vulnerable to climate change impacts—including extreme weather events—compared to urban areas, with high levels of variability by place and region [62]. And for rural communities dependent on agriculture, climate impacts can be multiscale, impacting both economic livelihoods and social processes [63]. Given this relationship between rural areas and increased potential for experiencing extreme weather impacts, we form the following hypothesis:

H7. Respondents living in rural areas will be more likely to report negative impacts from extreme weather events.

To answer our research questions and test our hypotheses, we surveyed a representative sample of the U.S. public and asked respondents to report their level of negative impacts from six extreme event types in the past three years.

The remainder of this article is summarized as follows. First, we describe our survey data and analytical methods used to identify groups of respondents negatively impacted by extreme weather. Next, we provide a summary of self-reported extreme weather events impacts across the general population as well as provide descriptions of types of extreme events experienced across different regions of the United States. We then present findings on the relationship between our selected sociodemographic characteristics and negative impacts from extreme events. Finally, we interpret our findings and identify limitations, as well as discuss policy implications and proposed future research.

2. Data and methods

2.1 Data collection

We use survey data collected through the AmeriSpeak bi-weekly Omnibus panel of the U.S. public, funded and operated by NORC at the University of Chicago. Survey participants were recruited from a probability-based panel that was randomly generated via address-based sampling and designed to be representative of the U.S. household population. To recruit survey participants for the AmeriSpeak panel, NORC contacts households by U.S. mail, telephone, and using field interviewers that conduct in-person recruitment. This results in panels with coverage of approximately 97 percent of the U.S. household population. Those populations who are more likely to be excluded from the sample have P.O. box only addresses, addresses that are not included in the USPS Delivery Sequence File, or live in newly built dwellings. For more detailed information about the AmeriSpeak panel and methodology, see [64] and for examples of recent research that applies survey data acquired from AmeriSpeak panels, see [65–67].

Our survey was administered online and by phone to 1071 participants who were 18 years or older from September 10–12, 2021 and included questions about extreme weather event impacts alongside other sociodemographic questions. Probability-based samples of this size are adequate for generating general population estimates and have even been shown to outperform much larger samples acquired using convenience-based sampling [68]. The overall margin of error for our survey sample was +/- 3.93 percentage points at the 95 percent confidence level. See Table J in S1 Text for a comparison between our survey sample composition and national U.S. population estimates.

This study was reviewed by the Oregon State University Human Research Protection Program (IRB-2019-0137) and received an exempt determination. NORC, the survey vendor, obtained written informed consent from study participants and de-identified all data prior to transmission to the authors.

2.2 Survey measures

Self-reported impacts from extreme weather events, our primary measure in this research, is formed from the multi-item survey question "How negatively impacted were you by you the following extreme events in the past three years?" with response categories 1 = "Not at all impacted", 2 = "Slightly impacted", 3 = "Moderately impacted", 4 = "Very impacted" and 5 = "Extremely impacted" for six extreme event types or type combinations. These six extreme event item descriptions include "Extreme cold / winter storms" (mean = 2.059, std. dev. = 1.162), "Extreme heat" (mean = 2.475, std. dev. = 1.264), "Extreme rainfall / flooding" (mean = 1.815, std. dev. = 1.055), "Hurricanes" (mean = 1.551, std. dev. = 0.978), "Wildfires" (mean = 1.674, std. dev. = 1.101), and "Tornadoes" (mean = 1.449, std. dev. = 0.911). When combined into a single mean composite index, average negative impacts from event types are 1.841 (std. dev. = 0.759), a value closest to the "Slightly impacted" category. For a reproduction of the original survey question, see Box A in S1 Text. We acknowledge that conceptualizations of self-reported impacts are subjective and could include everything from the severity and frequency of negative experiences to different types of impacts including monetary and health impacts. In this research we sought to balance impact specificity and generalizability, seeking to develop an overall understanding of impacts using a parsimonious set of survey items that anyone in the U.S. can respond to. For examples of survey research that asked about more specific impacts, such as physical harm, from single named events, see [22, 24].

We also assess how these self-reported impacts relate to sociodemographic characteristics, specifically gender, race/ethnicity, household income, education, age, and rurality, described in detail in Table 1. Demographic characteristics are formed into the following variables: female (= 46.4% vs. male), 65 or older (= 22.1%), bachelor's degree or higher (= 35.4%), Black (= 11.5%), Hispanic (= 16.4%), and Below Federal poverty level (= 19.7%). To construct the poverty measure, we first used household size to assign a Federal Poverty Level threshold to each respondent [69] and then compared this Federal Poverty Level threshold to the respondent's reported household income. If the respondent's reported household income was below this threshold, they were identified as being below the Federal poverty level. Additionally, we also apply a measure of respondent residence in a rural area using the designation of non-metropolitan (= 18%). Lastly, we apply information about respondents' locations within Census Regions (n = 4) and Census Divisions (n = 9) (see Table 1 for more detail).

Table 1. Summary of measures, descriptions, descriptive statistics, and variables applied in this research.

Measure	Description	Descriptive statistics	Variable formation and type
Gender	Gender of respondent	Male = 53.6% Female = 46.4%	Female (46.4%) Binary: female = 1 vs. male = 0
Age	Age of respondent[1]	Mean = 49.3 Median = 49 Range = 18–92	65 or older (22.1%) Binary: 65 or older = 1; 64 or younger = 0
Household income	Household income of respondent	Ranging from categories 1 = "Less than $5,000" to 18 = "$200,000 or more" Mean = 9.77 Median = 10 or "$50,000 to $59,999"	Below Federal Poverty Level (19.7%) Binary: Below Federal Poverty level = 1; at or above level = 0
Educational attainment	Education level of the respondent	Less than High School = 5.1% High School graduate or equivalent = 16.8% Vocational/tech school/some college/ Associate's degree = 42.6% Bachelor's degree = 19.7% Post grad study / professional degree = 15.8%	Bachelor's degree or higher (35.4%) Binary: Bachelor's degree or higher = 1; no Bachelor's degree = 0
Race/ethnicity	Race/ethnicity of the respondent	White, non-Hispanic = 64.6% Black, non-Hispanic = 11.5% Other, non-Hispanic = 1.1% Hispanic = 16.5% Two or more categories, non-Hispanic, 3.5% Asian, non-Hispanic: 2.9%	Black (11.5%) Binary: Black = 1; else = 0 Hispanic (16.5%) Binary: Hispanic = 1; else = 0 White (64.6%) Binary: White = 1; else = 0
Rurality	A measure of urban or rural place of residence	Metropolitan = 82.0% Non-metropolitan = 18.0%	Non-metropolitan = 18.0% Binary: Non-metropolitan = 1; Metropolitan = 0
Geography	Location of respondent within Census Regions and Divisions	Census Region: Northeast (16.5%); Midwest (28.0%); South (32.9%); West (22.6%) Census Division: New England (4.8%); Mid-Atlantic (11.8%); East North Central (18.5%); West North Central (9.5%); South Atlantic (18.3%); East South Central (8.7%); Mountain (7.8%); Pacific (14.8%)	Region Categorical = 4 regions Division Categorical = 9 divisions

[1] Only respondents who were 18 years or older participated in the survey

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2.3 Analytical approach

We apply a multi-stage analytical approach in this research. After generating descriptive statistics for extreme weather event impacts across types and geographies, in our first stage of analysis we identify groups of respondents with similar levels of self-reported negative extreme weather event impacts using clustering. In our second stage of analysis we then apply the resulting extreme weather event impact clusters, alongside our measure of average negative event impacts, to examine differences across sociodemographic characteristics using bivariate and multivariate analysis approaches.

Clustering methods are frequently used to group survey respondents based on similarities in question responses [70], including grouping respondents with similar levels of reported experience with adverse events [71]. In the context of this research, we apply clustering to identify groups of respondents with a composite of similar extreme weather event impact experiences. To do so, we apply the k-means clustering algorithm [72] to an input of the six extreme weather event impact question responses and select the number of cluster centers using visual heuristics as guidance. To provide further interpretation of these clusters, we examine average extreme weather event impacts across respondents within each cluster and assign cluster names using their dominant event impacts. We choose a naming convention where dominant events impacts are identified when average event impacts within each cluster round to moderately impacted or higher.

After event impact clusters are identified, we use these clusters to analyze differences across sociodemographic characteristics in our second stage of analysis. These include chi-square tests for bivariate analysis, as well as multilevel modeling for multivariate analysis using the R package lme4 [73]. We use multilevel modeling to account for the spatial grouping of respondents within geographic areas [74], as different areas in the United States have differing levels of impacts from extreme weather event types. We conduct both binary logistic regression analysis (when the dependent variable is dichotomous) and linear multilevel regression analysis (when the dependent variable is continuous). For modeling impact clusters derived from k-means clustering obtained in the first stage of our analysis, we use a binary logistic regression where each impact cluster is a dependent variable, sociodemographic characteristics are modeled as first-level predictors (i.e., fixed effects) and Census Divisions are modeled second-level predictors as random effect intercepts. These first-level predictors include Black, Hispanic, Below Federal poverty threshold, Bachelor's degree or higher, Female, and Non–metropolitan area. Using these same first- and second-level predictors, we next model the mean composite index of reported extreme event impacts across all six event types as a dependent variable, using linear multilevel regression to accommodate the continuous dependent variable.

We also test multiple alternative model specifications, reported in Tables D, I in S1 Text. Using linear multilevel regression, we predict impacts from single extreme event types in separate models (Tables E–G in S1 Text). We also test various household income measures (Tables H, I in S1 Text) as well as model Census Divisions as fixed effects instead of random effects (Table D in S1 Text). We find that our main findings are robust to these alternative model specifications.

3. Results

Extreme heat is the most frequently self-reported event and has the highest proportion of respondents with the most severe negative impacts, with one quarter (25%) reporting either being very / extremely impacted and over half (52%) of respondents being slightly / moderately impacted (Fig 1). The next most frequently reported extreme event type is extreme cold and

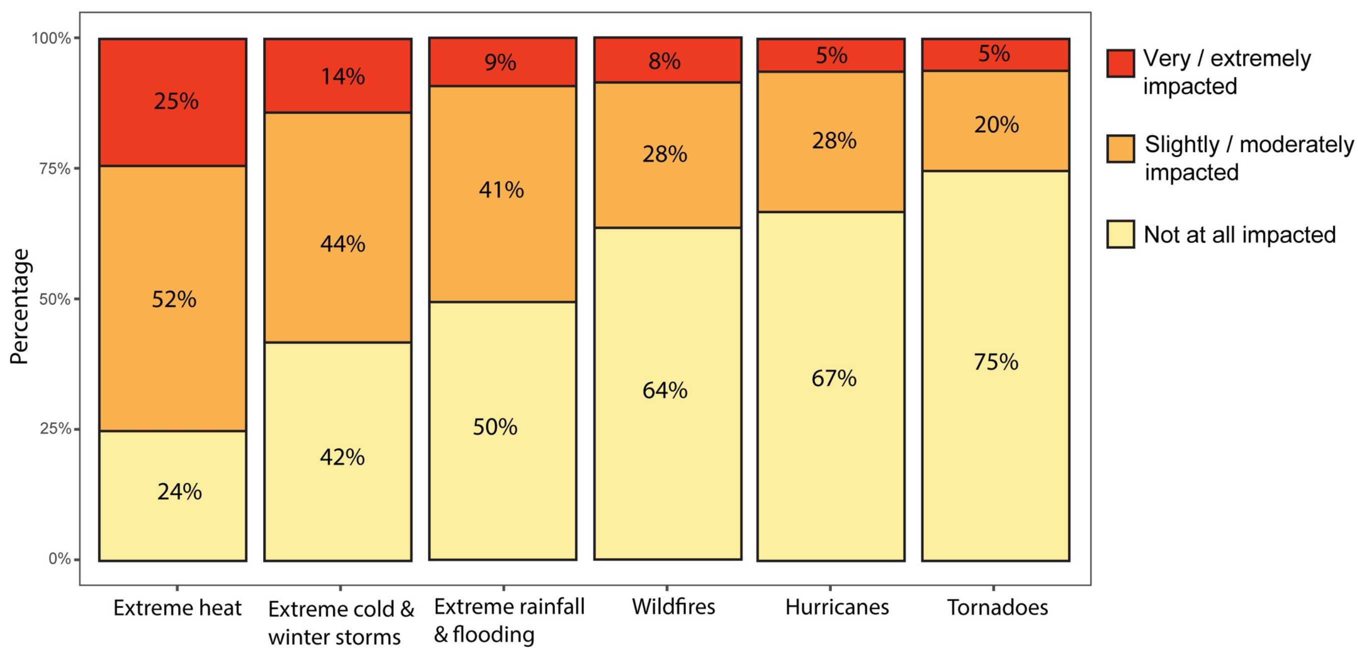

Fig 1. Frequency of respondents that self-reported negative impacts from extreme event types in the past three years. Categories of "Slightly / moderately impacted" and "Very / extremely impacted" are combined for display purposes.

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winter storms, with 14% reporting being very / extremely impacted and 44% reporting being slightly / moderately impacted. Hurricanes, extreme rainfall, tornadoes, and wildfires have similar frequencies for very / extremely impacted (5–9%), but extreme rainfall and flooding has a descriptively larger share of the slightly / moderately impacted (41%).

When event impacts categories from all six weather event types are averaged, the mean is 1.84, which is closest to the slightly impacted category (Fig 2A). A majority of these average impacts are distributed between not at all impacted and moderately impacted categories, with very few respondents indicating average extreme event impacts of very impacted or extremely impacted. This is consistent with expectations about population exposure to events that only impact certain U.S. geographies, unless respondents have moved to different regions of the U. S. within the three-year period prior to survey administration.

Looking across event types at the highest negative impacts reported, we find that 14.9% of respondents reported being extremely impacted by at least one extreme event, one-third (34.1%) reported being either very impacted or extremely impacted, and 59.0% reported being *at least* moderately impacted (Fig 2B). A substantial proportion of respondents—more than four out of five (86.3%)—reported being at least slightly impacted by an extreme weather event.

Given the comparatively large proportion of respondents that self-reported at least some negative impacts from extreme weather, we next explored the geographic distribution of these reported extreme weather impacts (Fig 3). We find there to be substantial regional and sub-regional heterogeneity, which partially reflects extreme weather event distributions across the United States. In the Northeast and Midwest regions, for example, there were relatively high reported extreme weather impacts from heat, cold, and rain events but low reported impacts from wildfire. However, in the West region, wildfire impacts were higher compared to the other regions, and even more so in the Pacific division which is consistent with recent destructive wildfires in California, Oregon, and Washington [13]. Another important pattern to note is the high extreme cold and winter storm impacts in the West South Central division within the South region. This area of the United States experienced widescale impacts from winter storms in early 2021 that left some areas of Texas without power and water for multiple days [15].

From these regional and divisional summaries, it is apparent that certain event types are more likely to result in reported impacts across different geographies, reflecting how exposure to these event types and combinations of events vary across the U.S. population. To better understand how respondents may have reported impacts from different event types and different levels of impact intensities, we formed four extreme weather impact groups of respondents using the k-means clustering algorithm. These impact groups are summarized by respondents'

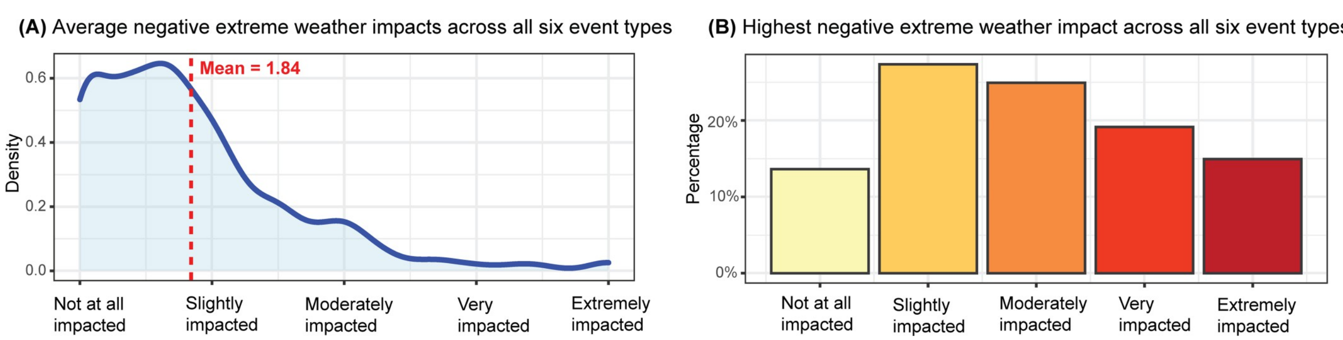

Fig 2. Density of average self-reported extreme weather impacts across event types (A). Highest level of extreme weather impact reported by respondents (B).

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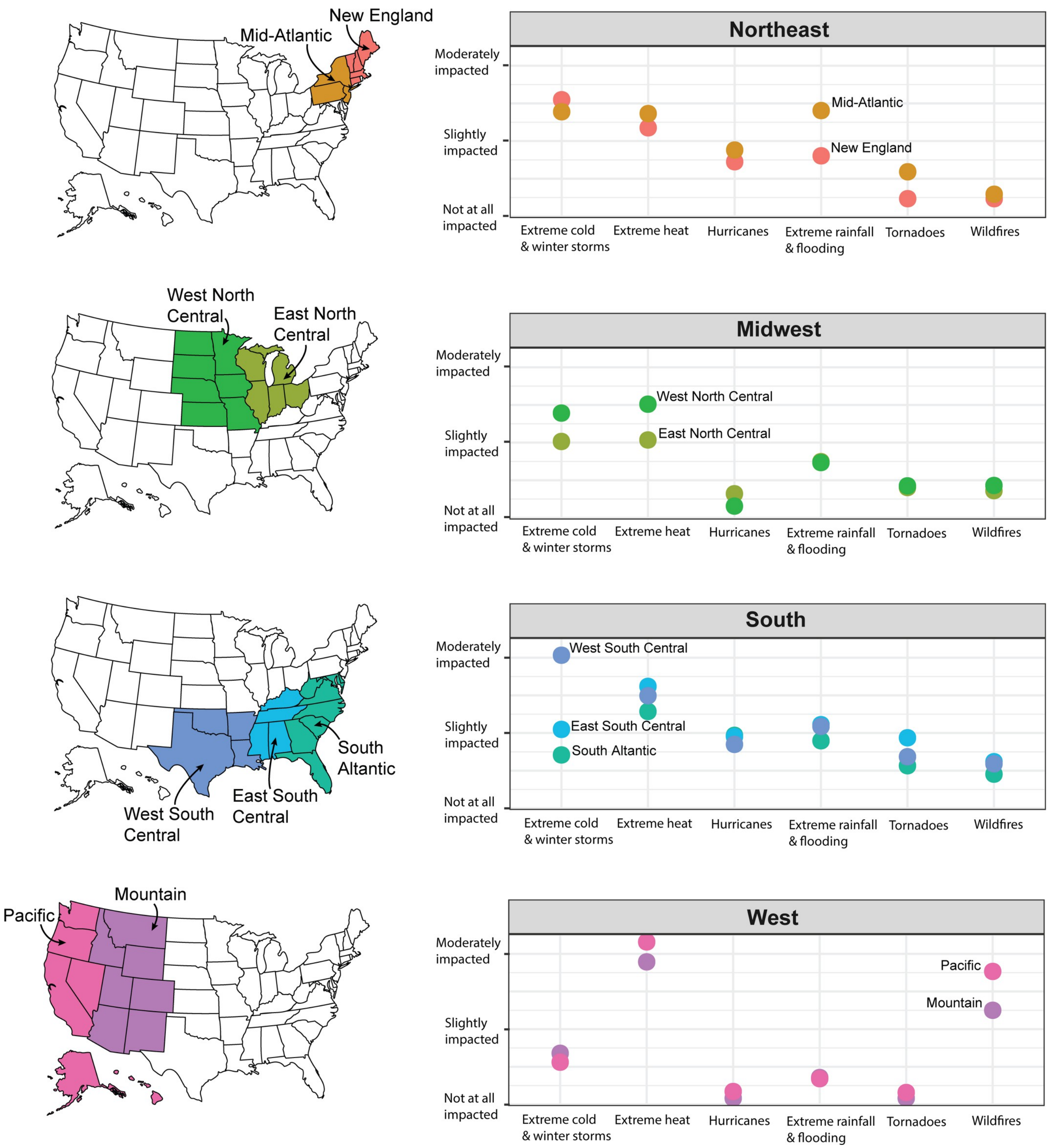

Fig 3. Average self-reported negative impacts from extreme weather events summarized by Census Division and organized per Census Region. Source of base map: Wikimedia Commons [75].

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average of reported impacts per event type (Fig 4). These four clusters are described as follows. The *High extreme weather impacts cluster* (11.4%) contains respondents who reported on average being at least moderately impacted by all extreme weather event types. The *Extreme heat /*

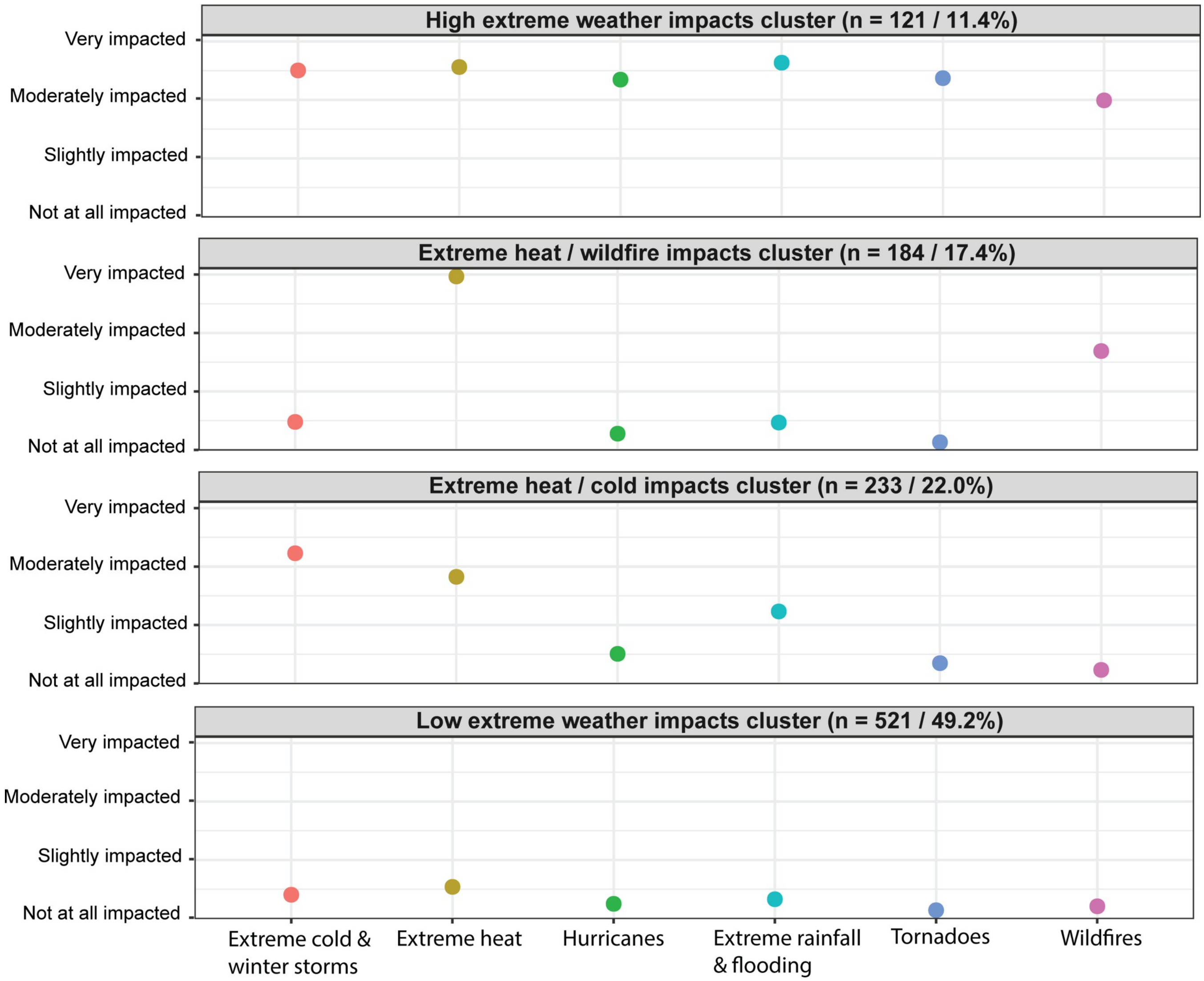

Fig 4. Extreme weather impact clusters identified using k-means algorithm summarized by the means of respondent self-reported impacts per event type.

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wildfire impacts cluster (17.4%) contains respondents who were on average very impacted by extreme heat, while also reporting impacts from wildfire. The *Extreme heat / cold impacts cluster* contains respondents that reported impacts primarily from heat and cold-related extreme events. And finally, *Low extreme weather impacts cluster* is the largest of the clusters (49.2% of respondents) and contains respondents who on average reported few negative impacts from extreme weather events.

When we examined these clusters by our selected sociodemographic characteristics (Fig 5), statistically significant differences in frequencies emerge for below Federal poverty level, white, Black, Hispanic, bachelor's degree, and female (chi-squared test, $p<0.05$). Over one-third of respondents in the high extreme weather impacts cluster live in a household with income below the Federal poverty level compared to 15% in the Low extreme weather impacts cluster. A similar pattern emerges for educational attainment, where 21% of respondents in the High extreme weather impacts cluster have a bachelor's degree or higher compared to 41% in the

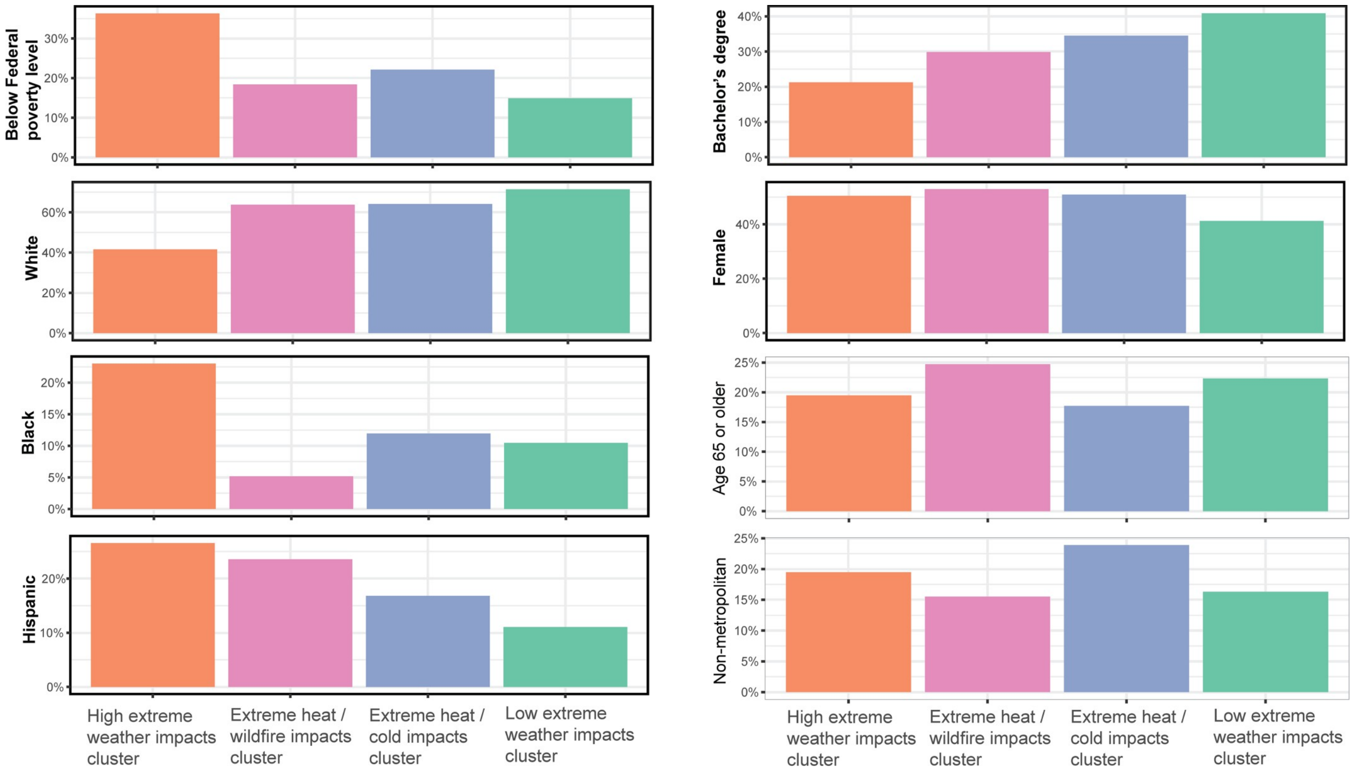

Fig 5. Binary sociodemographic measures (measure = 1 vs. else = 0) summarized by extreme weather impact cluster. Each bar represents the percentage of respondents within each extreme weather impact cluster compared to the excluded category. There are statistically significant differences (chi-squared test, $p<0.05$) across impact clusters for Below Federal poverty level, Black, Hispanic, White, Bachelor's degree, and Female, indicated by bolded text and borders.

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Low extreme impacts cluster. We also observe similar patterns for our measures of race/ethnicity, with the percentage of Black and Hispanic respondents in the High extreme weather impacts cluster nearly double that of the Low extreme weather impacts cluster. Lastly, there are differences across gender, with fewer female respondents in the Low extreme weather impacts cluster compared to the other impact clusters.

We next predicted the likelihood of extreme weather cluster membership using binary logistic multilevel regression (Fig 6). Similar to conclusions from Fig 5, substantial differences emerged for some of our sociodemographic measures across impact clusters. Those in the highest extreme weather impact cluster are 2.56 times more likely to be Black ($p<0.001$), 2.62 times more likely to be Hispanic ($p<0.001$), and 1.89 times more likely to be living in a household with income below the Federal poverty level ($p<0.01$), even after controlling for geographic area using Census Division random effects. We also find that respondents in the high extreme weather impact cluster are less likely to hold a bachelor's degree ($p<0.05$) and that some of the impact clusters have a higher likelihood of including female respondents (Extreme heat / wildfire impacts clusters, $p<0.01$) or are more likely to contain males (Low extreme weather impacts cluster, $p<0.01$). Finally, we find that respondents with the lowest reported extreme weather experience (i.e., Low extreme weather impacts cluster) are more likely to live in metropolitan areas ($p<0.05$). We do not, however, find any relationship between age and cluster membership.

In addition to predicting these impact clusters, we also predicted average self-reported impacts across all six event types (Fig 7, Fixed Effects). Our findings reinforce the conclusions

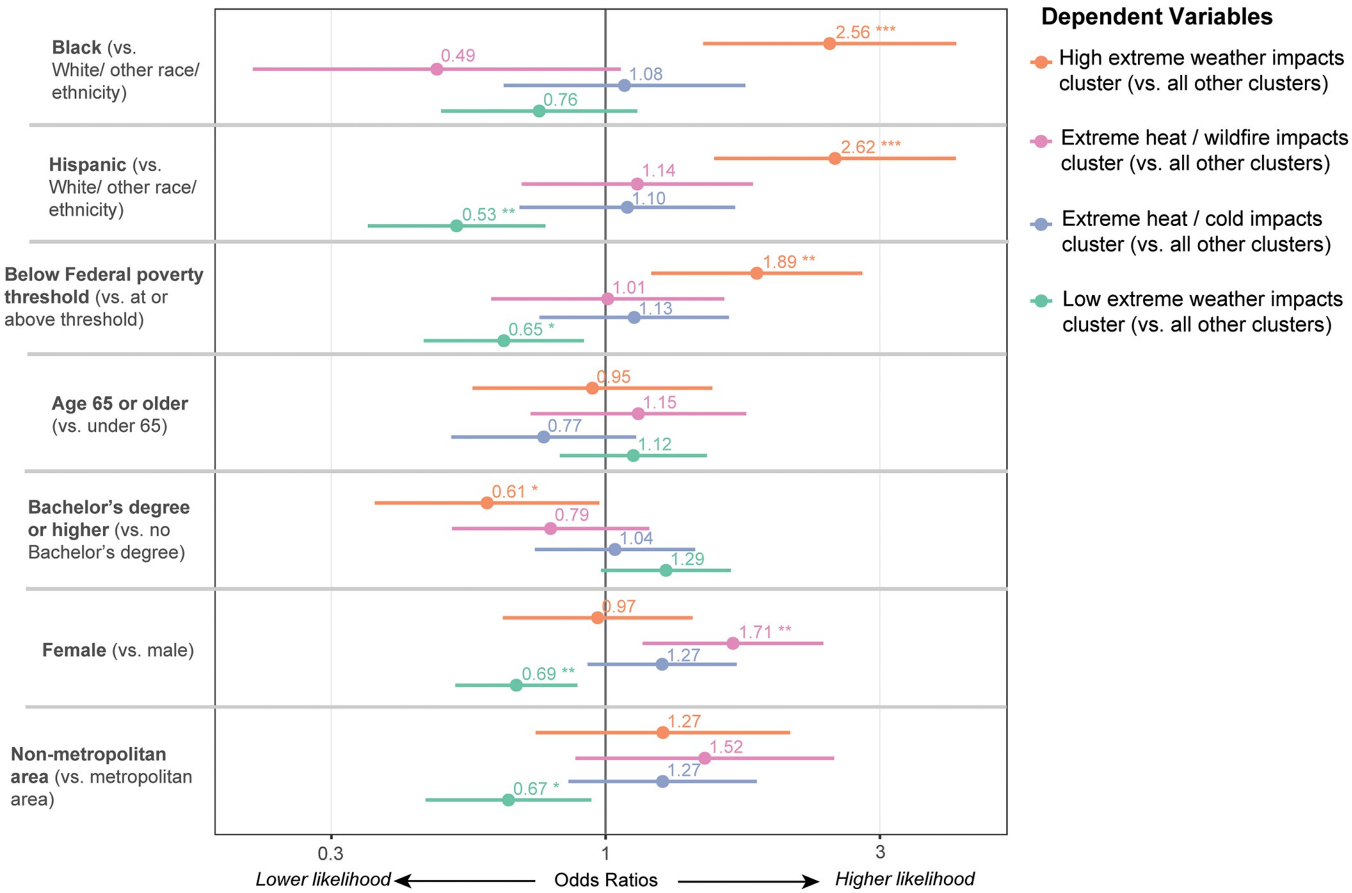

Fig 6. Binary logistic multilevel regression models predicting likelihood of extreme weather impacts cluster membership with Census Division random effects. Points represent odds ratios and lines 95% confidence intervals, with statistical significance levels indicated by p-value thresholds of $^{*}<0.05$, $^{**}<0.01$, and $^{***}<0.005$. Full model results, including standard errors, can be found in the Tables A, B in S1 Text.

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from these clustering results and show that even with extreme event experience averaged across all six event types, respondents who identified as Black (b = 0.26; $p<0.001$), Hispanic (b = 0.25; $p<0.001$), and live in households with income below the poverty level (0.30; $p<0.001$) reported more severe average impacts. We also find that living in a non-metropolitan area is related to higher average impacts, mirroring some of the previous findings in Fig 6 that being in a metropolitan area is related to membership in the Low extreme weather impacts cluster.

Modeling average event impacts also allows for easier interpretation of model random effect estimates, which, in our study, indicate *where*, on average, respondents reported comparatively more or less impacts after accounting for modeled sociodemographic variables. Such an approach allows us to explore group-level variation in reported impacts that may be related to place-based or contextual characteristics [74]. In this research, these groups are delineated by Census Division (see Fig 3 for a mapping of Census Divisions). When we examine the random effect intercept estimates for Census Divisions (Fig 7, Random Effects), we identify three differentially impacted geographical areas: the West South Central and Mid-Atlantic divisions, which are associated with comparatively higher negative extreme weather experiences, and East North Central, which is associated with comparatively lower reported extreme event impacts.

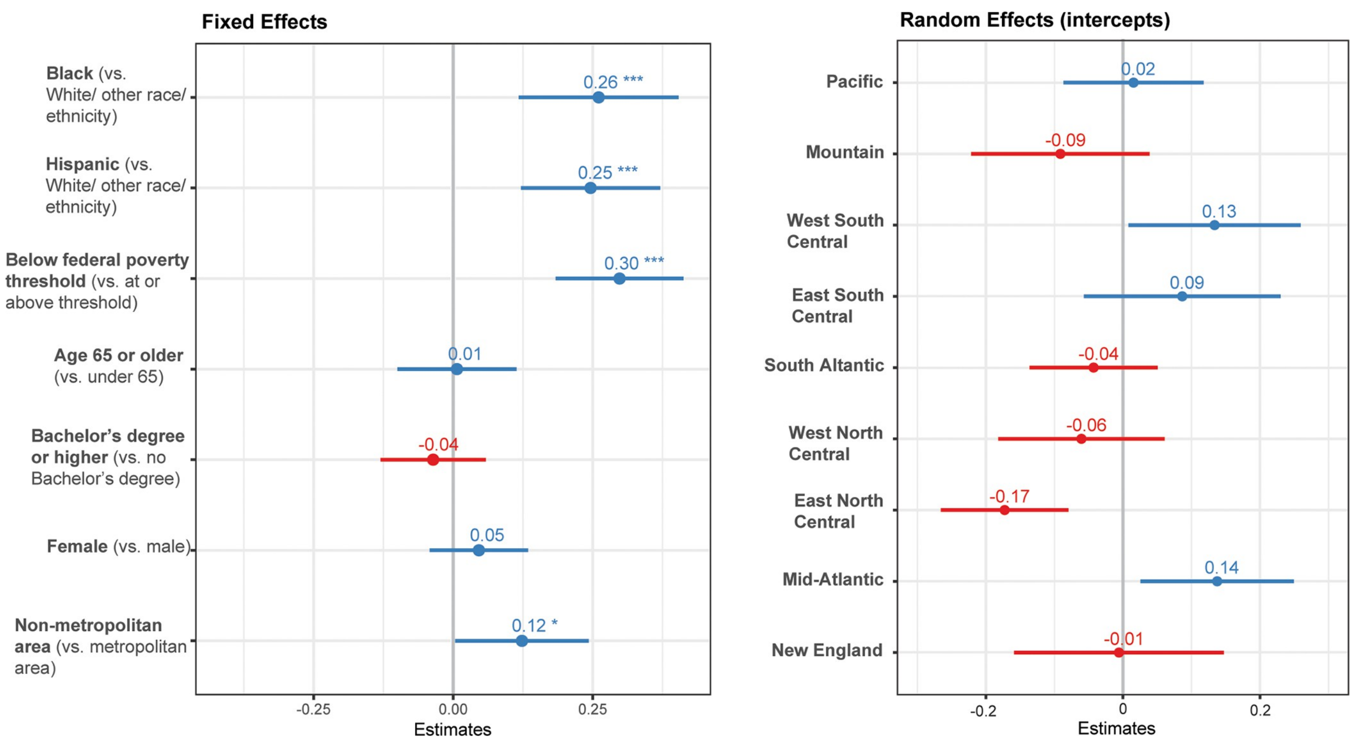

Fig 7. Linear multilevel regression models predicting average self-reported extreme weather impacts across all six extreme weather event types. Points represent linear coefficient estimates and lines 95% confidence intervals with statistical significance levels indicated by *p*-value thresholds of $^{*}<0.05$, $^{**}<0.01$, and $^{***}<0.005$. Full model results, including standard errors, can be found in the Table C in S1 Text.

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4. Discussion

We find that a large proportion of the American public self-reported being negatively impacted by extreme weather events in the past three years. An overwhelming majority (86%) of our representative sample of the U.S. public reported being at least slightly impacted by an extreme event and one-third (34%) reported being either very or extremely impacted by one or more extreme event. These extreme weather experience estimates are higher than other national polling conducted during approximately the same time period [26], although a direct comparison cannot be made because we asked about experience over a longer time horizon (3 years vs. 1 year), the level of negative impact experienced, and multiple event types. Moreover, our findings could be capturing very recent trends in extreme weather experience. In 2021, more than 40 percent of Americans were living in counties impacted by climate disasters and more than 80 percent experienced a heat wave [76]. We also found that self-reports of impacts from extreme weather events are related to region, with respondents from certain areas of the U.S. being more likely to report impacts from certain event types, notably extreme heat and wildfire impacts in the West, cold events in the South, and extreme rainfall / flooding in the Midwest, consistent with extreme events exposure in these regions. However, after controlling for sociodemographic factors in modeling and using measures of event impacts that allow for grouping respondents into impact clusters or as an average of extreme event impacts, we did not find geographic location to be the primary driver of reported extreme weather impacts among our participants.

When examining the association between sociodemographic characteristics and self-reported extreme event impacts, we find that respondents living in households with income below the poverty level, as well as respondents who are Black or Hispanic, reported more severe negative impacts from extreme weather events, leading us to accept our first three hypotheses (accept H1, H2, & H3). We did not, however, find that respondent age related to reported impacts from extreme weather events (reject H4). We also find that female respondents and those with lower educational attainment reported more negative extreme weather impacts in some of our analysis, leading us to partially accept these hypotheses (partially accept H5 & H6) as these results are not consistent across all analytical approaches. We find similar results for our respondents from rural areas: we partially accept our hypothesis (partially accept H7) as the lowest impact cluster was more likely to have metropolitan residents and we also uncovered a relationship—albeit weaker than poverty and race/ethnicity—to living in a non-metropolitan area and higher average levels of reported extreme weather impacts.

Our findings suggest that many people in the U.S. feel they are being negatively impacted by extreme weather events, though these perceptions differ across subgroups. Most prominently, people of color and the poor–groups identified as being more vulnerable to extreme events and disasters in previous literature [10, 27]–reported more negative impacts. Our research only considers self-reported impacts from extreme weather events and does not make any assessment about the objectivity of these reports or seek to identify vulnerable populations. Additionally, we do not consider some other potential demographic factors related to vulnerability, such as respondents with disabilities [77], who might also report being disproportionately impacted and should be a focus of future research.

While we asked respondents about negative impacts from extreme weather events within the past three years, there is likely a recency bias in their responses, with recent event experiences being more likely to be recalled [78]. Indeed, our survey was administered during hurricane season, only a few weeks after Hurricane Ida impacted the Gulf and East Coasts, the fifth costliest tropical cyclone in terms of damages in the history of United States [79]. However, there were a record 20 separate weather/climate disaster events with losses that exceeded $1 billion dollars in 2021 [80], including a winter storm in the deep south and Texas, wildfires across the western U.S., and tornado outbreaks in December after our survey was administered. Thus, any time period in which national surveying is conducted could be influenced by recent events.

Furthermore, we did not collect more specific information about self-reported negative extreme weather impacts, such as if they are related to health, property damage, lost income, etc., some of which may have different levels of impact severity for respondents with different sociodemographic characteristics. We know that, for example, in the wake of Hurricane Sandy, different population groups were impacted in different ways [81], so measuring these impacts with more specificity in future studies could help better understand these dimensions.

Indeed, there is a tradeoff in our approach. While we were able to ask questions relevant to a national sample about multiple different types of events, we were unable to target specific geographies with more specific questions about extreme event experience. This makes it challenging to relate negative reported impacts to named events. Longitudinal research designs, using repeated sampling of the same respondent, may be able to overcome some of these challenges [82], but linking perceptions of negative impacts with measures of objective impacts will likely remain an ongoing challenge [25]. Additionally, further work should be done to develop survey measures that include more impact specificity (e.g., type of impact, severity, frequency, etc.) while maintaining generalizability to multiple event types and avoiding respondent fatigue.

Our research also suggests that self-reported impacts from extreme weather events could augment objective measures, such as economic loss and health outcomes, which are themselves difficult to accurately assess [83]. Such self-reports could prove particularly important because some weather impacts have been shown to be underreported by the media and government agencies, such as recurrent household flooding [84], and are also found to disproportionately impact the financially insecure and communities of color [85]. In this respect, some impacts from extreme weather that may have been hidden through conventional reporting methods could become clearer through regular national surveys of the general public. That being said, being more specific about what constitutes an extreme event, an on-going area of scholarship [7], could help provide more precision about perceived event impacts, as well as lay the groundwork for developing subjective vs. objective comparisons. However, such efforts should not invalidate the reported experiences of those impacted by events, as they likely represent real hardships and loss. Indeed, those who have more cumulative experience with hardship and loss, especially among the most vulnerable, may even have lower levels of self-reported impacts from events compared to those with less historical experience and greater means of recovering from them. Therefore, understanding the factors related to these differentially reported impacts should be an on-going effort of both the academic and policy communities, especially with respect to understanding their relationship to objective impact measures.

Climate change is already changing the frequency and severity of extreme weather events and will continue to do so in the future without comprehensive global efforts to reduce carbon emissions. While there is substantial uncertainty about population exposure to future extreme weather events, unusual or abnormal weather events may become more common, exposing populations to weather impacts that they may not have much prior experience with or preparation for (e.g., smoke from Western wildfires impacting populations in Midwest and Northeastern states) [86]. Moreover, future impacts could be even further exacerbated by the risks posed by compound events, both weather and non-weather related [12, 87]. These realities suggest that we could be reaching an inflection point where regular national-level surveying of the U.S. public about their perceived experiences with extreme weather may be a necessary component of gauging population impacts and providing information to assist in policy responses. And while disaster preparedness and climate change adaptation planning may be different across regions, planning efforts should account for how different populations may be disproportionately impacted given the new extreme weather threats posed by climate change.

Supporting information

S1 Text.
(PDF)

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Author Contributions

Conceptualization: Chad Zanocco, June Flora, Hilary Boudet.

Formal analysis: Chad Zanocco.

Funding acquisition: Hilary Boudet.

Writing – original draft: Chad Zanocco.

Writing – review & editing: Chad Zanocco, June Flora, Hilary Boudet.

References

1. Guterres A. Secretary-General's statement on the IPCC Working Group 1 Report on the Physical Science Basis of the Sixth Assessment | United Nations Secretary-General. 2021 [cited 18 Oct 2021]. Available: https://www.un.org/sg/en/content/secretary-generals-statement-the-ipcc-working-group-1-report-the-physical-science-basis-of-the-sixth-assessment
2. Diffenbaugh NS, Burke M. Global warming has increased global economic inequality. PNAS. 2019; 116: 9808–9813. https://doi.org/10.1073/pnas.1816020116 PMID: 31010922
3. Taconet N, Méjean A, Guivarch C. Influence of climate change impacts and mitigation costs on inequality between countries. Climatic Change. 2020; 160: 15–34. https://doi.org/10.1007/s10584-019-02637-w
4. Thomas K, Hardy RD, Lazrus H, Mendez M, Orlove B, Rivera-Collazo I, et al. Explaining differential vulnerability to climate change: A social science review. WIREs Climate Change. 2019; 10: e565. https://doi.org/10.1002/wcc.565 PMID: 31007726
5. Bellprat O, Guemas V, Doblas-Reyes F, Donat MG. Towards reliable extreme weather and climate event attribution. Nat Commun. 2019; 10: 1732. https://doi.org/10.1038/s41467-019-09729-2 PMID: 30988387
6. National Academies of Sciences E. Attribution of Extreme Weather Events in the Context of Climate Change. 2016. https://doi.org/10.17226/21852
7. van Oldenborgh GJ, van der Wiel K, Kew S, Philip S, Otto F, Vautard R, et al. Pathways and pitfalls in extreme event attribution. Climatic Change. 2021; 166: 13. https://doi.org/10.1007/s10584-021-03071-7
8. Bathiany S, Dakos V, Scheffer M, Lenton TM. Climate models predict increasing temperature variability in poor countries. Science Advances. 2018; 4: eaar5809. https://doi.org/10.1126/sciadv.aar5809 PMID: 29732409
9. USGCRP. Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II. Washington, DC, USA: 1515; 2018. Available: https://nca2018.globalchange.gov
10. Cutter SL, Boruff BJ, Shirley WL. Social Vulnerability to Environmental Hazards*. Social Science Quarterly. 2003; 84: 242–261. https://doi.org/10.1111/1540-6237.8402002
11. Shi L, Moser S. Transformative climate adaptation in the United States: Trends and prospects. Science. 2021; 372: eabc8054. https://doi.org/10.1126/science.abc8054 PMID: 33927053
12. Wilhelmi OV, Howe PD, Hayden MH, O'Lenick CR. Compounding hazards and intersecting vulnerabilities: experiences and responses to extreme heat during COVID-19. Environ Res Lett. 2021; 16: 084060. https://doi.org/10.1088/1748-9326/ac1760
13. Fountain H. California's Wildfires Had an Invisible Impact: High Carbon Dioxide Emissions—The New York Times. 2021 [cited 18 Oct 2021]. Available: https://www.nytimes.com/2021/09/21/climate/wildfire-emissions-climate-change.html
14. Livingston I. Punishing heat waves peaking in Northwest and Northeast to ease this weekend. Washington Post. 2021. Available: https://www.washingtonpost.com/weather/2021/08/13/heat-wave-northeast-northeast/. Accessed 18 Oct 2021.
15. Hauser C, Sandoval E. Death Toll From Texas Winter Storm Continues to Rise. The New York Times. 14 Jul 2021. Available: https://www.nytimes.com/2021/07/14/us/texas-winter-storm-deaths.html. Accessed 18 Oct 2021.
16. Eavis P, Penn I. Why Louisiana's Electric Grid Failed in Hurricane Ida. The New York Times. 17 Sep 2021. Available: https://www.nytimes.com/2021/09/17/business/energy-environment/hurricane-ida-entergy-power-outage-new-orleans.html. Accessed 18 Oct 2021.
17. Lieberman-Cribbin W, Gillezeau C, Schwartz RM, Taioli E. Unequal social vulnerability to Hurricane Sandy flood exposure. J Expo Sci Environ Epidemiol. 2021; 31: 804–809. https://doi.org/10.1038/s41370-020-0230-6 PMID: 32398778
18. Silveira S, Kornbluh M, Withers MC, Grennan G, Ramanathan V, Mishra J. Chronic Mental Health Sequelae of Climate Change Extremes: A Case Study of the Deadliest Californian Wildfire. International Journal of Environmental Research and Public Health. 2021; 18: 1487. https://doi.org/10.3390/ijerph18041487 PMID: 33557397
19. Cutler MJ, Marlon JR, Howe PD, Leiserowitz A. The Influence of Political Ideology and Socioeconomic Vulnerability on Perceived Health Risks of Heat Waves in the Context of Climate Change. Weather, Climate, and Society. 2018; 10: 731–746. https://doi.org/10.1175/WCAS-D-17-0105.1
20. Silver A, Andrey J. The Influence of Previous Disaster Experience and Sociodemographics on Protective Behaviors during Two Successive Tornado Events. Weather, Climate, and Society. 2014; 6: 91–103. https://doi.org/10.1175/WCAS-D-13-00026.1

21. Boudet H, Giordono L, Zanocco C, Satein H, Whitley H. Event attribution and partisanship shape local discussion of climate change after extreme weather. Nat Clim Chang. 2020; 10: 69–76. https://doi.org/10.1038/s41558-019-0641-3

22. Zanocco C, Boudet H, Nilson R, Flora J. Personal harm and support for climate change mitigation policies: Evidence from 10 U.S. communities impacted by extreme weather. Global Environmental Change. 2019; 59: 101984. https://doi.org/10.1016/j.gloenvcha.2019.101984

23. Esplin ED, Marlon JR, Leiserowitz A, Howe PD. "Can You Take the Heat?" Heat-Induced Health Symptoms Are Associated with Protective Behaviors. Weather, Climate, and Society. 2019; 11: 401–417. https://doi.org/10.1175/WCAS-D-18-0035.1

24. Zanocco C, Boudet H, Nilson R, Satein H, Whitley H, Flora J. Place, proximity, and perceived harm: extreme weather events and views about climate change. Climatic Change. 2018; 149: 349–365. https://doi.org/10.1007/s10584-018-2251-x

25. Howe PD, Boudet H, Leiserowitz A, Maibach EW. Mapping the shadow of experience of extreme weather events. Climatic Change. 2014; 127: 381–389. https://doi.org/10.1007/s10584-014-1253-6

26. Funk C, Tyson A. 67% of Americans perceive a rise in extreme weather, but partisans differ over government efforts to address it. In: Pew Research Center [Internet]. 14 Oct 2021 [cited 21 Oct 2021]. Available: https://www.pewresearch.org/fact-tank/2021/10/14/67-of-americans-perceive-a-rise-in-extreme-weather-but-partisans-differ-over-government-efforts-to-address-it/

27. Benevolenza MA, DeRigne L. The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature. Journal of Human Behavior in the Social Environment. 2019; 29: 266–281. https://doi.org/10.1080/10911359.2018.1527739

28. Karaye IM, Horney JA. The Impact of Social Vulnerability on COVID-19 in the U.S.: An Analysis of Spatially Varying Relationships. American Journal of Preventive Medicine. 2020; 59: 317–325. https://doi.org/10.1016/j.amepre.2020.06.006 PMID: 32703701

29. Marshall J, Wiltshire J, Delva J, Bello T, Masys AJ. Natural and Manmade Disasters: Vulnerable Populations. In: Masys AJ, Izurieta R, Reina Ortiz M, editors. Global Health Security: Recognizing Vulnerabilities, Creating Opportunities. Cham: Springer International Publishing; 2020. pp. 143–161. https://doi.org/10.1007/978-3-030-23491-1_7

30. Hallegatte S, Vogt-Schilb A, Rozenberg J, Bangalore M, Beaudet C. From Poverty to Disaster and Back: a Review of the Literature. EconDisCliCha. 2020; 4: 223–247. https://doi.org/10.1007/s41885-020-00060-5

31. Leichenko R, Silva JA. Climate change and poverty: vulnerability, impacts, and alleviation strategies. WIREs Climate Change. 2014; 5: 539–556. https://doi.org/10.1002/wcc.287

32. Fothergill A, Peek LA. Poverty and Disasters in the United States: A Review of Recent Sociological Findings. Natural Hazards. 2004; 32: 89–110. https://doi.org/10.1023/B:NHAZ.0000026792.76181.d9

33. Lee D, Jung J. The growth of low-income population in floodplains: A case study of Austin, TX. KSCE J Civ Eng. 2014; 18: 683–693. https://doi.org/10.1007/s12205-014-0205-z

34. Markhvida M, Walsh B, Hallegatte S, Baker J. Quantification of disaster impacts through household well-being losses. Nat Sustain. 2020; 3: 538–547. https://doi.org/10.1038/s41893-020-0508-7

35. Masozera M, Bailey M, Kerchner C. Distribution of impacts of natural disasters across income groups: A case study of New Orleans. Ecological Economics. 2007; 63: 299–306. https://doi.org/10.1016/j.ecolecon.2006.06.013

36. Hallegatte S, Rozenberg J. Climate change through a poverty lens. Nature Clim Change. 2017; 7: 250–256. https://doi.org/10.1038/nclimate3253

37. Andrasfay T, Goldman N. Reductions in 2020 US life expectancy due to COVID-19 and the disproportionate impact on the Black and Latino populations. PNAS. 2021;118. https://doi.org/10.1073/pnas.2014746118 PMID: 33446511

38. Cronin CJ, Evans WN. Excess mortality from COVID and non-COVID causes in minority populations. PNAS. 2021;118. https://doi.org/10.1073/pnas.2101386118 PMID: 34544858

39. Memmott T, Carley S, Graff M, Konisky DM. Sociodemographic disparities in energy insecurity among low-income households before and during the COVID-19 pandemic. Nat Energy. 2021; 6: 186–193. https://doi.org/10.1038/s41560-020-00763-9

40. Fothergill A, Maestas EGM, Darlington JD. Race, Ethnicity and Disasters in the United States: A Review of the Literature. Disasters. 1999; 23: 156–173. https://doi.org/10.1111/1467-7717.00111 PMID: 10379098

41. Sabatello M, Jackson Scroggins M, Goto G, Santiago A, McCormick A, Morris KJ, et al. Structural Racism in the COVID-19 Pandemic: Moving Forward. The American Journal of Bioethics. 2021; 21: 56–74. https://doi.org/10.1080/15265161.2020.1851808 PMID: 33345745

42. Hsu A, Sheriff G, Chakraborty T, Manya D. Disproportionate exposure to urban heat island intensity across major US cities. Nat Commun. 2021; 12: 2721. https://doi.org/10.1038/s41467-021-22799-5 PMID: 34035248

43. Wilson B. Urban Heat Management and the Legacy of Redlining. Journal of the American Planning Association. 2020; 86: 443–457. https://doi.org/10.1080/01944363.2020.1759127

44. Witze A. Racism is magnifying the deadly impact of rising city heat. Nature. 2021; 595: 349–351. https://doi.org/10.1038/d41586-021-01881-4 PMID: 34262220

45. Brunkard J, Namulanda G, Ratard R. Hurricane Katrina Deaths, Louisiana, 2005. Disaster Medicine and Public Health Preparedness. 2008; 2: 215–223. https://doi.org/10.1097/DMP.0b013e31818aaf55

46. Dobbins J, Tabuchi H. Texas Blackouts Hit Minority Neighborhoods Especially Hard. The New York Times. 16 Feb 2021. Available: https://www.nytimes.com/2021/02/16/climate/texas-blackout-storm-minorities.html. Accessed 21 Oct 2021.

47. Tormos-Aponte F, Garcia-Lopez G, Painter MA. Analysis | Hurricanes may not discriminate, but governments and utility companies do, our research finds. Washington Post. Available: https://www.washingtonpost.com/politics/2021/09/23/hurricanes-may-not-discriminate-governments-utility-companies-do-our-research-finds/. Accessed 10 Nov 2021.

48. Adams RM, Evans CM, Mathews MC, Wolkin A, Peek L. Mortality From Forces of Nature Among Older Adults by Race/Ethnicity and Gender. J Appl Gerontol. 2020; 0733464820954676. https://doi.org/10.1177/0733464820954676 PMID: 32909520

49. Peek L. Age. 2nd ed. In: Thomas DSK, Phillips BD, Lovekamp WE, Fothergill A, editors. Social Vulnerability to Disasters. 2nd ed. CRC Press; 2013. pp. 167–198.

50. Tierney K. Chapter 6. Communities and Societies at Risk. The Social Roots of Risk: Producing Disasters, Promoting Resilience. Stanford University Press; 2014. pp. 125–159. https://doi.org/10.1515/9780804791403-007

51. Poor Newberry L., elderly and too frail to escape: Paradise fire killed the most vulnerable residents. In: Los Angeles Times [Internet]. 10 Feb 2019 [cited 18 Oct 2021]. Available: https://www.latimes.com/local/lanow/la-me-ln-camp-fire-seniors-mobile-home-deaths-20190209-story.html

52. Enarson E, Fothergill A, Peek L. Gender and Disaster: Foundations and New Directions for Research and Practice. In: Rodríguez H, Donner W, Trainor JE, editors. Handbook of Disaster Research. Cham: Springer International Publishing; 2018. pp. 205–223. https://doi.org/10.1007/978-3-319-63254-4_11

53. Bradshaw S, Fordham M. Chapter 14—Double Disaster: Disaster through a Gender Lens. In: Shroder JF, Collins AE, Jones S, Manyena B, Jayawickrama J, editors. Hazards, Risks, and Disasters in Society. Boston: Academic Press; 2015. pp. 233–251. https://doi.org/10.1016/B978-0-12-396451-9.00014–7

54. Gearhart S, Perez-Patron M, Hammond TA, Goldberg DW, Klein A, Horney JA. The Impact of Natural Disasters on Domestic Violence: An Analysis of Reports of Simple Assault in Florida (1999–2007). Violence and Gender. 2018; 5: 87–92. https://doi.org/10.1089/vio.2017.0077

55. Neumayer E, Plümper T. The Gendered Nature of Natural Disasters: The Impact of Catastrophic Events on the Gender Gap in Life Expectancy, 1981–2002. Annals of the Association of American Geographers. 2007; 97: 551–566. https://doi.org/10.1111/j.1467-8306.2007.00563.x

56. Muttarak R, Lutz W. Is Education a Key to Reducing Vulnerability to Natural Disasters and hence Unavoidable Climate Change? Ecology and Society. 2014;19. Available: https://www.jstor.org/stable/26269470

57. Frankenberg E, Sikoki B, Sumantri C, Suriastini W, Thomas D. Education, Vulnerability, and Resilience after a Natural Disaster. Ecol Soc. 2013; 18: 16. https://doi.org/10.5751/ES-05377-180216 PMID: 25170339

58. Hoffmann R, Blecha D. Education and Disaster Vulnerability in Southeast Asia: Evidence and Policy Implications. Sustainability. 2020; 12: 1401. https://doi.org/10.3390/su12041401

59. Lutz W, Muttarak R, Striessnig E. Universal education is key to enhanced climate adaptation. Science. 2014; 346: 1061–1062. https://doi.org/10.1126/science.1257975 PMID: 25430758

60. Kapucu N, Hawkins CV, Rivera FI. Disaster Preparedness and Resilience for Rural Communities. Risk, Hazards & Crisis in Public Policy. 2013; 4: 215–233. https://doi.org/10.1002/rhc3.12043

61. Prelog A, Miller L. Perceptions of Disaster Risk and Vulnerability in Rural Texas. Journal of Rural Social Sciences. 2013;28. Available: https://egrove.olemiss.edu/jrss/vol28/iss3/1

62. Lal P, Alavalapati JRR, Mercer ED. Socio-economic impacts of climate change on rural United States. Mitig Adapt Strateg Glob Change. 2011; 16: 819. https://doi.org/10.1007/s11027-011-9295-9

63. Greene C. Broadening understandings of drought–The climate vulnerability of farmworkers and rural communities in California (USA). Environmental Science & Policy. 2018; 89: 283–291. https://doi.org/10.1016/j.envsci.2018.08.002

64. NORC. Technical overview of the AmeriSpeak panel NORC's probability-based household panel. NORC at the University of Chicago. 2021. Available: https://amerispeak.norc.org/Documents/Research/AmeriSpeak%20Technical%20Overview%202019%2002%2018.pdf

65. Nagler RH, Vogel RI, Gollust SE, Rothman AJ, Fowler EF, Yzer MC. Public perceptions of conflicting information surrounding COVID-19: Results from a nationally representative survey of U.S. adults. PLOS ONE. 2020; 15: e0240776. https://doi.org/10.1371/journal.pone.0240776 PMID: 33085719

66. Schneider JA, Taylor BG, Hotton AL, Lamuda PA, Ozik J, Lin Q, et al. National variability in Americans' COVID-19 protective behaviors: Implications for vaccine roll-out. PLOS ONE. 2021; 16: e0259257. https://doi.org/10.1371/journal.pone.0259257 PMID: 34739498

67. Latkin CA, Dayton L, Yi G, Colon B, Kong X. Mask usage, social distancing, racial, and gender correlates of COVID-19 vaccine intentions among adults in the US. PLOS ONE. 2021; 16: e0246970. https://doi.org/10.1371/journal.pone.0246970 PMID: 33592035

68. Bradley VC, Kuriwaki S, Isakov M, Sejdinovic D, Meng X-L, Flaxman S. Unrepresentative big surveys significantly overestimated US vaccine uptake. Nature. 2021; 600: 695–700. https://doi.org/10.1038/s41586-021-04198-4 PMID: 34880504

69. U.S. Census Bureau. Poverty Thresholds. In: Census.gov [Internet]. 2020 [cited 22 Oct 2021]. Available: https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

70. Zakharov K. Application of k-means clustering in psychological studies. TQMP. 2016; 12: 87–100. https://doi.org/10.20982/tqmp.12.2.p087

71. Zanocco C, Flora J, Rajagopal R, Boudet H. When the lights go out: Californians' experience with wildfire-related public safety power shutoffs increases intention to adopt solar and storage. Energy Research & Social Science. 2021; 79: 102183. https://doi.org/10.1016/j.erss.2021.102183

72. Everett B, Landau S, Leese M, Stahl D. Cluster analysis 5th ed. John Wiley & Sons; 2011.

73. Bates D, Mächler M, Bolker B, Walker S. Fitting Linear Mixed-Effects Models using lme4. arXiv:14065823 [stat]. 2014 [cited 27 Mar 2019]. Available: http://arxiv.org/abs/1406.5823

74. Gelman A. Multilevel (Hierarchical) Modeling: What It Can and Cannot Do. Technometrics. 2006; 48: 432–435. https://doi.org/10.1198/004017005000000661

75. Wikimedia Commons. Blank map of the states, created specifically for use with thick borders, without labels. 2007. Available: https://commons.wikimedia.org/wiki/File:Blank_US_map_borders.svg

76. Kaplan S, Ba Tran A. More than 40 percent of Americans live in counties hit by climate disasters in 2021. Washington Post. 5 Jan 2022. Available: https://www.washingtonpost.com/climate-environment/2022/01/05/climate-disasters-2021-fires/. Accessed 2 Mar 2022.

77. Gaskin CJ, Taylor D, Kinnear S, Mann J, Hillman W, Moran M. Factors Associated with the Climate Change Vulnerability and the Adaptive Capacity of People with Disability: A Systematic Review. Weather, Climate, and Society. 2017; 9: 801–814. https://doi.org/10.1175/WCAS-D-16-0126.1

78. Fownes JR, Allred SB. Testing the Influence of Recent Weather on Perceptions of Personal Experience with Climate Change and Extreme Weather in New York State. Weather, Climate, and Society. 2019; 11: 143–157. https://doi.org/10.1175/WCAS-D-17-0107.1

79. NOAA. U.S. Billion-Dollar Weather and Climate Disasters. 2021. Available: https://www.ncdc.noaa.gov/billions/

80. Smith AB. U.S. Billion-dollar Weather and Climate Disasters, 1980—present (NCEI Accession 0209268). NOAA National Centers for Environmental Information; 2022. https://doi.org/10.25921/STKW-7W73

81. Madajewicz M. Who is vulnerable and who is resilient to coastal flooding? Lessons from Hurricane Sandy in New York City. Climatic Change. 2020; 163: 2029–2053. https://doi.org/10.1007/s10584-020-02896-y

82. Andrews TM, Smirnov O. Who feels the impacts of climate change? Global Environmental Change. 2020; 65: 102164. https://doi.org/10.1016/j.gloenvcha.2020.102164

83. Boakye J, Murphy C, Gardoni P, Kumar R. Which consequences matter in risk analyis and disaster assessment? International Journal of Disaster Risk Reduction. 2022; 71: 102740. https://doi.org/10.1016/j.ijdrr.2021.102740

84. Sampson NR, Price CE, Kassem J, Doan J, Hussein J. "We're Just Sitting Ducks": Recurrent Household Flooding as An Underreported Environmental Health Threat in Detroit's Changing Climate. International Journal of Environmental Research and Public Health. 2019; 16: 6. https://doi.org/10.3390/ijerph16010006

85. Larson PS, Gronlund C, Thompson L, Sampson N, Washington R, Steis Thorsby J, et al. Recurrent Home Flooding in Detroit, MI 2012–2020: Results of a Household Survey. International Journal of

Environmental Research and Public Health. 2021; 18: 7659. https://doi.org/10.3390/ijerph18147659 PMID: 34300113

86. Burke M, Driscoll A, Heft-Neal S, Xue J, Burney J, Wara M. The changing risk and burden of wildfire in the United States. PNAS. 2021;118. https://doi.org/10.1073/pnas.2011048118 PMID: 33431571

87. Zscheischler J, Westra S, van den Hurk BJJM, Seneviratne SI, Ward PJ, Pitman A, et al. Future climate risk from compound events. Nature Clim Change. 2018; 8: 469–477. https://doi.org/10.1038/s41558-018-0156-3