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Characterizing community water systems exposed to wildfire in the Western U.S.

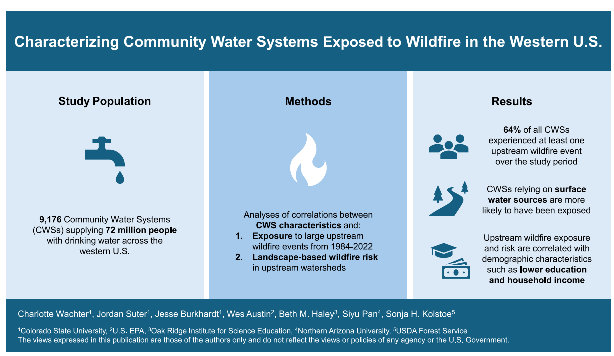
Charlotte Wachter [a,*], Jordan F. Suter [a], Jesse Burkhardt [a], Wes Austin [b,1], Beth M. Haley [c,2], Siyu Pan [d], Sonja H. Kolstoe [e,3]

[a] Department of Agricultural and Resource Economics, Colorado State University, United States of America
[b] National Center for Environmental Economics, U.S. Environmental Protection Agency, United States of America
[c] Oak Ridge Institute for Science and Education, US Department of Energy, Oak Ridge, TN, United States of America
[d] W. A. Franke College of Business, Northern Arizona University, United States of America
[e] Pacific Northwest Research Station, USDA Forest Service, United States of America

HIGHLIGHTS

- 64 % of water systems experienced at least one upstream wildfire from 1984 to 2022.
- Water systems relying on surface water sources had more frequent wildfire exposure.
- Wildfire-exposed systems serve more socially vulnerable populations.
- High wildfire hazard potential is correlated with lower education and income levels.
- Urban systems and those with more facilities face greater wildfire risk.

GRAPHICAL ABSTRACT



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ABSTRACT

Wildfires have increased in size and severity and so has concern over how wildfires impact water security. The current literature suggests that wildfires may negatively impact surface water quality and community drinking water systems dependent on surface water as their drinking water source. Yet few studies consider the implications for the populations served by these downstream community drinking water systems. This research contributes to a more comprehensive understanding of water security by characterizing community water systems (CWSs) historically exposed to wildfire as well as their future potential wildfire risk in the western United States. Of the 9176 CWSs, which supply approximately 72 million people in the western United States with drinking water, we find that 64 % of all CWSs (serving approximately 60 million people) in our sample experienced at least one upstream wildfire between 1984 and 2022. We also find that CWSs that rely on surface water sources and serve large populations are more likely to have been exposed to upstream wildfires. Lastly, using

* Corresponding author.
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[3] The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

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CWS service area boundaries, we find that upstream wildfire exposure and landscape-based wildfire hazard potential are correlated with demographic characteristics such as lower education and household income.

1. Introduction

Rising temperatures and prolonged droughts contribute to longer wildfire seasons as well as larger and more severe wildfires (Sommerfeld et al., 2018; Westerling, 2016), which may impact forested watersheds important to drinking water (Mack et al., 2022). Concerns about the complex and interconnected effects of wildfire have increased in recent decades as wildfire activity, including the length of the wildfire season, number of fires, area burned, and fire severity, has increased rapidly in many areas of the world, including the western U.S. (Abatzoglou and Kolden, 2013; Abatzoglou and Williams, 2016; Reilly et al., 2017). These rising trends in wildfire activity are projected to continue in some regions due to changing climate, increasing population, and historic fire suppression activities (Flannigan et al., 2013; Gao et al., 2021; Moritz et al., 2012; Senande-Rivera et al., 2022). Concurrently, there have been growing concerns about the economic, social, and environmental impacts of increasingly severe wildfires (Bowman et al., 2017; Schoennagel et al., 2017; Stevens-Rumann et al., 2018; Wear et al., 2024).

Wildfires can produce rapid changes in catchment hydrological and biogeochemical processes, which can challenge treatment plants beyond their operational capacity and have substantial, long-term implications for the provision of safe drinking water (Emelko et al., 2011; Hohner et al., 2019; Paul et al., 2022). Impacts of wildfires on surface water quality characteristics and aquatic ecosystems can persist for years (e.g., Hallema et al., 2018a; Hallema et al., 2018b; Paul et al., 2022; Rhoades et al., 2019; Rust et al., 2019). In some cases, wildfires may result in increased infrastructure and operating costs, service disruptions, or outages (Emelko et al., 2011; Hohner et al., 2018; Price et al., 2017). Paul et al. (2022) provide an overview of how the increase in wildfire hazard has led to growing concern over the impacts of wildfires on drinking water, as source water quality, treatment efficiency and costs, and physical infrastructure may be adversely affected post-fire. Paul et al. (2022) also note heterogeneity of impacts over regions for where studies have been conducted to date. Several studies have noted the need to include fire in local, regional, and global assessments of catchment vulnerability to the effects of disturbances on hydrologic processes and source water supply (Kinoshita et al., 2016; Martin, 2016; Robinne et al., 2018; Robinne et al., 2021). In the western U.S., many areas are both critical for the provision of water for domestic/beneficial uses and are exposed to increasing wildfire risk.

The impact of wildfire events on downstream public water systems can impose costs on communities via two primary channels, with the first being degraded quality of finished water, and the second being higher costs or water rates. Pennino et al. (2022) analyze the relationship between wildfire events, drinking water quality violations, and concentrations of select contaminants in drinking water across the United States. The authors found an increase in violations for nitrates, arsenic, and disinfection byproducts in the years following wildfire events in upstream watersheds; however, the data used in this analysis predate the major fires of the late 2010s and the historic 2020 wildfire season. Even if water quality degradation does not cause a violation, it still represents a cost to households as numerous studies have estimated positive household willingness to pay (WTP) for drinking water quality (e.g., Tanellari et al., 2015; Um et al., 2002). Even in the absence of stressors associated with wildfires, 3 to 10 % of CWSs do not achieve consistent compliance with the SDWA per studies done by Allaire et al. (2018) and Scanlon et al. (2023).[4] The 2017 Tubbs Fire and the 2018 Camp Fire highlighted a new concern for water utilities and their consumers—adverse effects from the wildfires on the water distribution networks—which were further exacerbated by the severity of the events (Proctor et al., 2020). Physical damage to existing water distribution system infrastructure may adversely affect water quality and impose economic costs on CWSs, as evidenced by the 2021 Marshall Fire (Whelton et al., 2023). Additionally, fluctuations in source water quality can significantly impact the cost of treating drinking water, and these costs can be passed on to communities in the form of higher water bills (Price and Heberling, 2018).

To date, studies on the implications of wildfires for drinking water have primarily focused on raw and finished water quality, with less attention given to the composition of impacted communities. Many of the papers that evaluate social vulnerability to natural disasters and other stochastic environmental and natural resource outcomes are built upon the methods by Flanagan et al. (2011) who developed a Social Vulnerability Index (SVI) for Disaster Management (Painter et al., 2024).[5] To date, several studies have used or constructed a SVI and have shown that measures of social vulnerability may differ by context (e.g., Palaiologou et al., 2019; Scanlon et al., 2023; Sanchez et al., 2023; Tascon-Gonzalez et al., 2020). For example, a study by Scanlon et al. (2023) studied the linkage between health-based drinking water violations and social vulnerability in the U.S. using the Center for Disease Control (CDC)'s SVI and a modified SVI, which they calculated specific to drinking water quality, and found variation in the statistical significance of specific social characteristics based on the type of health-based violation.[6]

Although previous research has separately evaluated social vulnerability with respect to water availability and wildfire, no research we are aware of has analyzed social vulnerability regarding past wildfire

[4] The Safe Drinking Water Act (SDWA) and its subsequent amendments regulate over 90 containments as regulated containments that are recognized or what they proxy for are understood to pose a harm to public health (42 U.S.C. §300f et seq., 1974). Allaire et al. (2018) find that 3 to 10 % of community water systems in the United States incurred health-based violations in any given year over their study period of 1982 to 2015. A recent study by Scanlon et al. (2023) analyzed SDWA violation data from 2018 to 2020 and find that about 10 % of community water systems incurred health-based violations. The 1996 SDWA Amendment required community water systems to inform their customers about their water quality through an annual water quality report known as a consumer confidence report (CCR) by July 1st of every year starting in 1999.

[5] In subsequent work, Flanagan et al. (2018) describe the SVI index, known as the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry Social Vulnerability Index, which compares sociodemographic characteristics of spatial units (e.g., counties, census tracts) and assigns percentile values to each unit (CDC/ATSDR SVI) (CDC/ATSDR, 2022; Painter et al., 2024).

[6] Scanlon et al. (2023) found that most health-based violations are related to disinfectant and disinfectant by-product violations, followed by naturally occurring contaminants such as arsenic and radionuclides, and anthropogenic contaminants, namely nitrates.

exposure and wildfire hazard potential for community water systems (CWSs) and the populations they serve.[7] Beyond variation in social vulnerability, CWSs also vary in terms of water source (surface water or groundwater), number of water sources, type of water treatment technology, and watershed characteristics. Combining social vulnerability measures with CWS characteristics allows us to explore the potential for heterogeneous impacts, which will provide critical insights into the distribution of community vulnerability characteristics and wildfire impacts to drinking water.

The objective of this research is to study the correlations between the composition of communities served by CWSs and whether they have experienced at least one wildfire event at least 1000 acres in size in their upstream source water area between 1984 and 2022, as well as landscape-based wildfire hazard potential of upstream source watersheds.[8] We begin in Section 2, CWS Characteristics and Wildfire, by analyzing the correlations between CWS system-level characteristics and historic wildfire exposure as well as current wildfire hazard potential. In Section 3, Social Vulnerability and Wildfire, we examine whether CWS service-area level measures of social vulnerability are correlated with historic wildfire exposure and current wildfire hazard potential. Finally, in Section 4, Discussion, we summarize our main results, relate our findings to the existing literature on social vulnerability and other environmental hazards, and detail potential directions for future research. The correlations we observe in our analyses may be used to inform the inclusion of such metrics in subsequent analyses seeking to understand how communities may be impacted by wildfires through changes in drinking water (e.g., water treatment costs and finished water quality).

2. CWS characteristics and wildfire

This study analyzes CWS exposure to wildfire by integrating various spatial and demographic datasets. First, we use information in the data from the Safe Drinking Water Information System (SDIWS) to characterize CWSs (U.S. EPA, 2024a, 2025b). Then, using SDWIS data and the Drinking Water Application to Protect Source Waters (DWMAPS), we map each CWS to the relevant subwatershed at the scale of hydrologic unit code 12 (HUC 12) (U.S. EPA, 2025a). Next, we map upstream watersheds to account for both in-watershed and upstream wildfire burn areas, which are calculated using wildfire perimeters from the Monitoring Trends in Burn Severity (MTBS) program (MTBS Direct Download: Burned Areas Boundaries Dataset., 2022). We also overlay watersheds with the 2023 Wildfire Hazard Potential (WHP) index and extract summary statistics for each CWS's upstream area (U.S. Forest Service Fire Modeling Institute, 2024). Finally, we present trends in CWS exposure to wildfire over time and analyze variations in exposure and WHP as a function of CWS characteristics. All analyses were completed in R version 4.5.0 (R Core Team, 2024) using ggplot version 3.5.2 to create figures (Wickham et al., 2025) and gtsummary version 2.2.0 to create tables (Sjoberg et al., 2021).

2.1. Data and methods

SDWIS provides data for 430,391 public water systems (PWSs) across the United States. We use these data to characterize water systems based on the number and location of source facilities, regulatory category, source water type, geographic location, and service area population demographics.

After filtering to the western U.S., we further restrict our sample to CWSs. CWSs are a subset of PWSs that serve at least fifteen service connections used by year-round residents or that regularly serve at least twenty-five year-round residents (U.S. EPA, 2025b). We focus on CWSs rather than including all PWSs because we are most concerned about wildfire impacts to residents who rely on their local water system for drinking water provision year-round.[9] The final dataset from SDWIS contains 9176 CWSs that are associated with 31,123 active source facilities in the western U.S. Facilities are physical structures or infrastructure associated with a CWS, such as reservoirs, treatment plants, and intakes.[10] We utilize CWS source facility information provided at the HUC 12 geography, available through DWMAPS (U.S. EPA, 2025a). If a system has source facilities in more than one watershed, we consider both source watersheds as starting points and account for the burned upstream areas from both source watershed mappings.

We utilize watershed boundaries from the Watershed Boundary Dataset (WBD), a national hydrologic unit (HU) dataset, to link CWSs to upstream wildfires (U.S. Geological Survey, 2025).[11] We use HUC 12 watershed delineations, the subwatershed level, which are the smallest delineation complete for the U.S. ranging from 10,000 to 40,000 acres in size (USGS and USDA, 2012). We consider all 32,440 HUC 12 watersheds in the western U.S. as "origin" watersheds.[12] Then, using a variable in the data that indicates the HUC 12 immediately downstream, we work backward to map which watersheds are upstream from each origin watershed. Once we have mapped the watersheds immediately upstream, we use these watersheds as the origin watersheds and iteratively work backward to look further upstream. The output is each HUC 12 watershed's unique identifier as well as identifiers for all upstream watersheds, delineated by the number of watershed levels upstream from the original HUC.

We use the Burned Area Boundaries Dataset from MTBS to identify areas burned by wildfire. The Burned Area Boundaries Dataset is a shapefile of all wildland and prescribed fires at least 1000 acres in size from 1984 to 2022. Our analysis uses the fire boundaries to identify fires upstream from CWSs by overlaying the fire polygons with the HUC 12 watersheds and calculating the area burned within each watershed by year. Using the upstream watershed mapping, we relate fires to source watersheds by calculating the share of upstream area burned, up to five watersheds upstream. If a system has source facilities in more than one watershed, we review the calculated share of upstream area burned for

[7] Community water system (CWS) is one of the three categories of public water systems (PWSs) in the U.S., with the other two categories being transient non-community water system and non-transient non-community water system. As such, CWS is the only PWS type that focuses on serving residential households. A CWS is defined as "A PWS that serves at least 15 service connections used by year-round residents or regularly serves at least 25 year-round residents (e.g., homes, apartments and condominiums that are occupied year-round as primary residences)." (U.S. EPA, 2025b).

[8] See Figure A1 in the Appendix for a diagram depicting how CWSs and the populations they serve are exposed to wildfire impacts via drinking water sources, our research questions when examining CWS characteristics and service population demographics, and the analyses we use to explore these questions.

[9] A public water system (PWS) is a system for the provision to the public of piped water for human consumption, which has at least 15 service connections or regularly serves an average of at least 25 individuals at least 60 days out of the year. PWSs are categorized as either a CWS, a transient non-community water system (TNCWS), or a non-transient non-community water system (NTNCWS) (U.S. EPA, 2025b).

[10] Following documentation from SDWIS, we consider consecutive connections (CC), infiltration galleries (IG), intakes (IN), non-piped (NP), roof catchments (RC), reservoir (RS), springs (SP), wells (WL), and non-piped non-purchased (NN) as the types of facilities where water is sourced (U.S. EPA, 2025b).

[11] Publicly available from the U.S. Geological Survey (USGS): https://www.usgs.gov/national-hydrography/watershed-boundary-dataset.

[12] We refer to "origin" watersheds as the starting point for the upstream mapping process, which iteratively maps watersheds immediately upstream. It is important to distinguish "origin watersheds" from "source watersheds" as source watersheds are directly mapped to drinking water source facilities and origin watersheds are not.

each intake watershed and consider a system to have an upstream burn if at least one of the source watersheds has any upstream area burned. By mapping the wildfire occurrences to watershed boundaries, we can then measure the frequency of wildfire occurrence in the same watershed as a CWS source facility, one watershed upstream, two watersheds upstream, and up to five watersheds upstream.[13]

We use the 2023 Wildfire Hazard Potential (WHP) raster geospatial dataset from the USDA Forest Service Fire Modeling Institute to gauge landscape-based wildfire risk.[14] The WHP dataset is an index based on landscape conditions at the end of 2020 that quantifies the relative potential for high-intensity wildfire that may be difficult to manage (Scott et al., 2024). Areas with higher WHP values are more likely to experience extreme fire behavior (U.S. Forest Service Fire Modeling Institute, 2024). The WHP dataset is integrated with the Wildfire Risk to Communities project, and while WHP is not an explicit map of wildfire risk, WHP is a tool for long-term planning that depicts one component of wildfire hazard to communities (U.S. Forest Service Fire Modeling Institute, 2024). In our analysis, we extract the mean, median, and maximum WHP values for watersheds containing CWS source facilities and up to five watersheds upstream. The maximum WHP value is most correlated with our measure of wildfire exposure, so we use the maximum WHP for each CWS's upstream area (including the source watershed) as a measure of landscape-based wildfire risk.[15] In the case where a CWS has two distinct source watersheds and, thus, two distinct upstream areas, we consider the average WHP of the two. We use the established 2023 WHP classification scheme for the contiguous U.S. to classify maximum WHP values as very low, low, moderate, high, and very high (Scott et al., 2024). In our regression analysis in Section 3, Social Vulnerability and Wildfire, we use the log of maximum WHP to examine the correlations between CWS population characteristics and landscape-based wildfire risk. Note that as a result of incorporating available WHP data, we lose 2 CWSs from our sample, so tables and figures that report results for WHP have 9174 observations rather than 9176.

2.2. CWS summary statistics

Fig. 1 depicts CWS locations by population bin and primary water source while Table 1 provides CWS summary statistics. On average, CWSs that primarily rely on surface water serve more people, have more facilities, and are more likely to have mixed sources (both groundwater and surface water source facilities).[16] In the western U.S., 7617 CWSs serving approximately 18.3 million people rely on groundwater sources, while 1559 CWSs that rely on surface water sources serve approximately 53.4 million people.

Over the entire period from 1984 to 2022, 64.7 % (5935/9176) of CWSs in our sample experienced at least one wildfire event upstream, with 43.6 % (4004/9176) of CWSs experiencing a wildfire in the same HUC 12 watershed as their source facility(s). Fig. 2 illustrates trends in the percentage of CWSs exposed to upstream wildfire from 1984 to 2022. From this figure, we can see that the percentage of both surface water and groundwater CWSs exposed to wildfire increases over the study period.[17] Furthermore, the percentage of surface water CWSs exposed to wildfire each year tends to be higher than the percentage of groundwater CWSs exposed to wildfire. This supports the notion that surface water CWSs are more likely to be exposed to upstream wildfire events.

Fig. 3 maps CWS locations colored by the percentage of years each system experienced an upstream wildfire burn and by each system's maximum WHP value. This figure highlights that many systems did not experience any upstream wildfire burns between 1984 and 2022, but certain systems experienced upstream wildfire burns nearly every year. Additionally, systems with a higher percentage of years exposed to wildfire tend to have higher maximum WHP, although this correlation is notably weaker for systems in southern Idaho, central Utah, and southern Arizona.

Finally, we summarize differences in means for CWS characteristics in Table 2. CWSs that have experienced at least one wildfire serve more people and have more facilities, on average. This is also true for CWSs with maximum WHP classified as “High” or “Very High”. Urban and surface water CWSs account for a higher proportion of CWSs that have experienced an upstream wildfire, as well as a higher proportion of CWSs with High or Very High maximum WHP values.

3. Social vulnerability and wildfire

Populations served by CWSs are characterized using demographic and socioeconomic variables from the American Community Survey (ACS) 2016–2020 (5-year) data (U.S. Census Bureau, 2020). We use this data to calculate a CWS-level social vulnerability index (SVI) based on the approach used by Flanagan et al. (2018) for developing an SVI to measure community vulnerability to natural hazards used by the Centers for Disease Control and Prevention (CDC) (see CDC/ATSDR, 2022). We explore differences in means for CWS service area populations whose CWSs have (have not) experienced at least one upstream wildfire in the period 1984 to 2022, as well as differences in means for CWS service area populations with (without) High or Very High maximum WHP. We analyze CWS-level SVI values for the overall index and the four theme indices, as well as the individual demographic and socioeconomic variables used to construct the overall index. We also regress the probability of experiencing an upstream wildfire burn and the log(maximum WHP) on the CWS-level SVIs and indicator variables, while controlling for CWS characteristics.

3.1. Data and methods

To account for the spatial extent of the population served by a given CWS, we utilize CWS service area boundaries produced by the U.S. EPA's Office of Research and Development (U.S. EPA, 2024b). The EPA boundaries rely on explicit water service boundary geometries when available. There are EPA service area boundaries for 9176 CWSs in our dataset.

We overlay the CWS service area boundaries with demographic and socioeconomic data from the ACS to characterize populations served by each CWS. Table 3 provides a full list and description of the demographic and socioeconomic variables included in our analysis.

Painter et al. (2024) conducted a systematic scoping review of the SVI literature applied to natural hazards and highlighted such indices as

[13] The choice to map fires up to five watersheds upstream is arbitrary. Further research, beyond the scope of this study, is needed to investigate how burned area further upstream impacts drinking water and what an evidence-based upstream cutoff might be.

[14] Publicly available from the USDA Forest Service: https://www.fs.usda.gov/rds/archive/catalog/RDS-2020-0016-2.

[15] We estimated the Pearson correlation coefficient between the percentage of years a CWS was exposed to wildfire over our study period and log(max WHP) to be approximately 0.6, indicating that the two variables are moderately correlated. However, despite the correlation, we believe reporting results for both exposure and WHP is informative because the first provides information on communities that have been exposed to wildfire and the second provides information on future potential exposure.

[16] Mixed source means that the CWS drinking water is sourced from a combination of surface and groundwater sources (CDC, n.d).

[17] Fire detection methods have transitioned from reliance on human observers (e.g., reports by fire lookout towers, campers, hikers, etc.) to computerized methods leveraging satellite and remote sensing data (Pozo et al., 1997; Yang et al., 2024). This improvement in monitoring capabilities may assist in detecting fires sooner given advances in technology and detection algorithms (Yang et al., 2024).

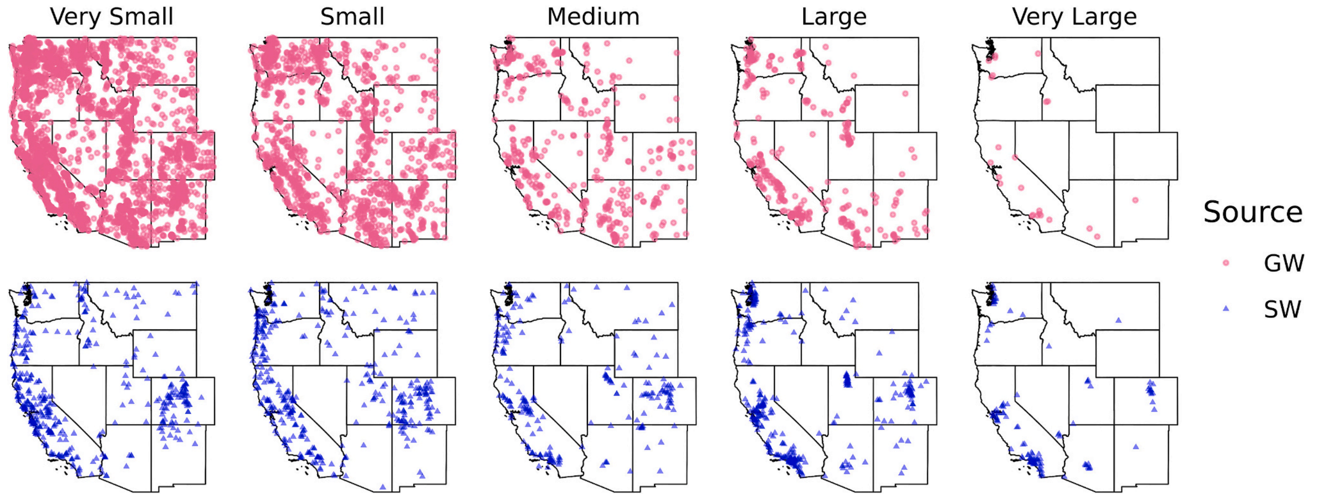

Fig. 1. Spatial distribution of CWSs by water source and size. The water source categories refer to groundwater and surface water as "GW" and "SW", respectively. The size categories refer to the population served with "Very Small" corresponding to 500 or less people served, "Small" corresponding to 501–3300 people served, "Medium" corresponding to 3301–10,000 people served, "Large" corresponding to 10,000–100,000 people served, and "Very Large" corresponding to 100,000+ people served.

Table 1
Summary statistics of CWS characteristics.

CWS characteristic	All $N = 9{,}176$[a]	Source classification	
		GW $N = 7{,}617$[a]	SW $N = 1{,}559$[a]
Avg daily population served	7811.78 (63,640.67)	2401.14 (14,217.00)	34,247.25 (148,393.50)
Number of active source facilities	3.39 (6.00); Min: 1.00, Max: 206.00	2.80 (3.97); Min: 1.00, Max: 158.00	6.26 (11.17); Min: 1.00, Max: 206.00
Mixed source (indicator)	1288 / 9176 (14 %)	360 / 7617 (5 %)	928 / 1559 (60 %)
Urban (indicator)	5638 / 9176 (61 %)	4639 / 7617 (61 %)	999 / 1559 (64 %)

[a] Mean (SD); Min: Min, Max: Max; n / N (%).

a tool intended to help policymakers and emergency response planners identify and map communities that will most likely need support before, during, and after hazardous events such as severe weather, floods, and disease outbreaks. Flanagan et al. (2018) build on the SVI literature to develop an SVI index, known as the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry Social Vulnerability Index (CDC/ATSDR SVI) (CDC/ATSDR, 2022; Painter et al., 2024). The SVI characterizes each Census tract in the U.S. using a total of sixteen demographic and socioeconomic variables from the ACS, which are grouped into four related themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation. These themes represent different dimensions of social vulnerability. Each tract receives a percentile ranking for each variable, a percentile ranking for each theme, and an overall percentile ranking. The overall ranking is referred to as the overall SVI and relates how vulnerable a Census tract is relative to all other Census tracts in the U.S. For example, a tract with an SVI of 0.70 is considered more vulnerable than 70 % of other tracts; a tract with a socioeconomic status SVI of 0.70 is considered more vulnerable along the socioeconomic dimension than 70 % of other tracts.

CWS service areas often span multiple Census tracts, so we develop a modified version of the SVI that is based on CWS service area boundaries and refer to it as the "CWS SVI". The CWS SVI follows the same methodology but is at the service area level within our study area rather than the tract level. First, we overlay the CWS service area boundaries with Census tracts and calculate the proportion of the total service area covered by each tract for each service area. Then, we use these areas to assign weights to the different Census tracts and calculate area-weighted averages of the sixteen ACS demographic variables at the service area level. The area-weighted average demographic variables are grouped into the same four themes as the SVI and each service area receives a percentile ranking for each variable, a percentile ranking for each theme, and an overall percentile ranking. Similar to the SVI, these percentile rankings communicate how vulnerable a CWS is relative to all other CWSs in our sample. For example, a CWS with an overall CWS SVI of 0.70 is considered more vulnerable than 70 % of other CWSs in the western U.S. study area.

Finally, we utilize the 2023 Rural-Urban Continuum Codes (RUCC) from the U.S. Department of Agriculture (USDA) to create a variable to indicate if a CWS is in an "urban" area (Economic Research Service, United States Department of Agriculture, 2024). A dummy variable equal to 1 is assigned to a CWS service area if its boundary lies within a county that is defined as urban. Urban counties are defined as counties with a RUCC is less than or equal to 3. This follows documentation from USDA that identifies counties with RUCC is less than or equal to 3 as "metro" counties and counties with RUCC greater than or equal to 4 as "non-metro" counties (Economic Research Service, United States Department of Agriculture, 2024). If a CWS service area spans multiple counties, we assign the "urban" variable using the RUCC code from the county that accounts for most of the service area.

In Fig. 4, we map CWS locations by population bin colored by overall CWS SVI. This mapping highlights that socially vulnerable CWSs are not spatially concentrated in urban areas; rather, socially vulnerable CWSs are distributed across the study area.

3.2. Social vulnerability results

It is important to emphasize that the occurrence of a wildfire or the presence of a high WHP in an upstream watershed does not imply a causal relationship between social vulnerability and wildfire. Instead, the empirical analysis focuses on highlighting correlations between wildfire occurrences as well as landscape-based WHP in upstream watersheds and dimensions of social vulnerability in populations that are served by impacted CWSs.

3.2.1. Difference in means analysis of wildfire exposure and WHP

We examine the difference in means for variables of interest associated with CWSs that have (have not) been exposed to wildfire during

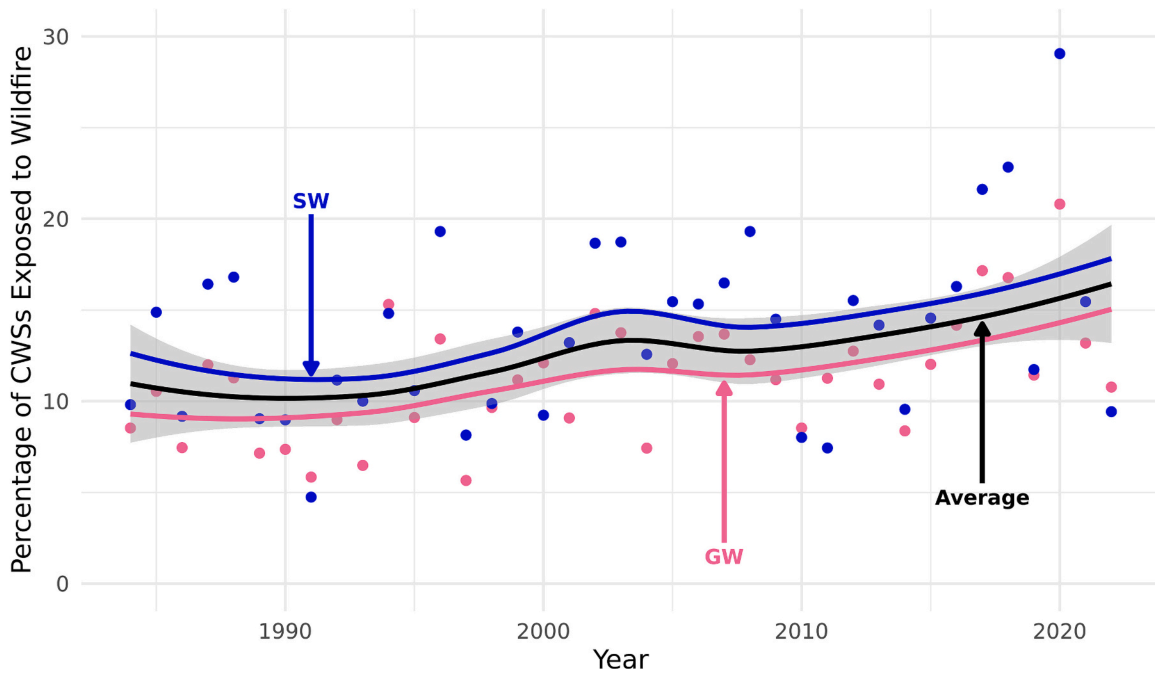

Fig. 2. Percentage of CWSs exposed to wildfire over time, overall (all CWSs) and by water source. Trend lines were fitted using local polynomial regression. The overall (average) trend line is shown in black, while trends for CWSs relying primarily on surface water (SW) and groundwater (GW) are shown in blue and pink, respectively.

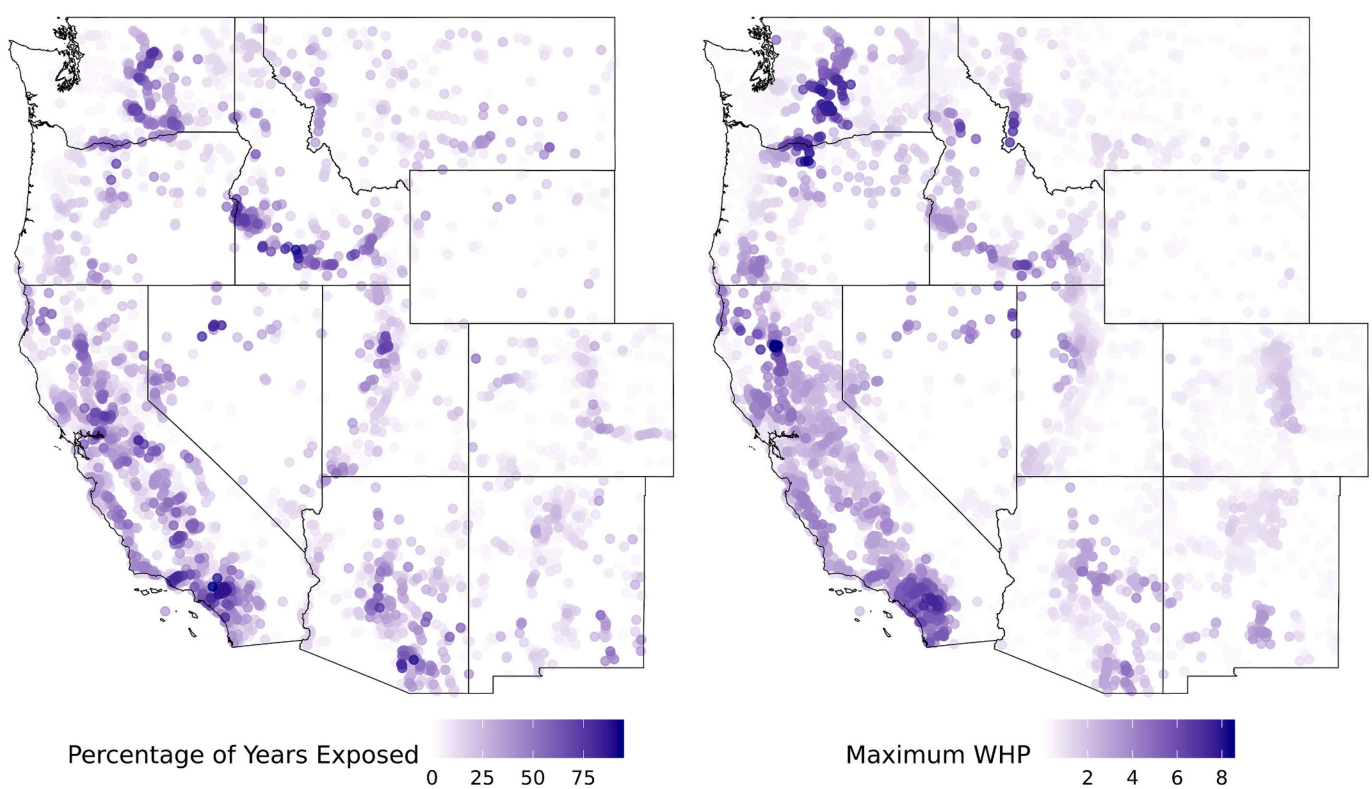

Fig. 3. Spatial distribution of CWSs by wildfire exposure (left panel) and WHP (right panel). WHP values range from 0 to 10 but are multiplied by 10,000 to preserve decimal points in the raw data download (Scott et al., 2024). In Fig. 3, Panel B, we divide the raw WHP values by 10,000.

the study period to assess differences between communities whose drinking water systems have been exposed to wildfire and those that have not. This analysis is complemented by comparable differences in means for CWSs with (without) High or Very High maximum WHP. To better understand the heterogeneity of impacts, we examine how community vulnerability to wildfire differs for CWSs that primarily rely on surface water and groundwater.

Fig. 5 depicts mean CWS SVI values for CWSs that experience any wildfire (upstream or within their intake watershed) within the period 1984 to 2022 as well as mean CWS SVI values for CWSs that have high or

Table 2
Difference-in-means for CWS characteristics.

CWS characteristic	Exposed to wildfire[a]		High or very high maximum WHP[b]	
	1 $N = 5{,}934$[c]	0 $N = 3{,}240$[c]	1 $N = 7{,}961$[c]	0 $N = 1{,}213$[c]
Avg daily population served	10,151.25 (76,480.50)	3531.74 (27,017.78)	8687.61 (68,063.83)	2076.11 (14,003.81)
Number of active source facilities	3.77 (7.08)	2.70 (3.06)	3.51 (6.32)	2.64 (3.06)
Mixed source (indicator)	932 / 5934 (16 %)	356 / 3240 (11 %)	1205 / 7961 (15 %)	83 / 1213 (7 %)
Surface water under SDWA (indicator)	1127 / 5934 (19 %)	432 / 3240 (13 %)	1467 / 7961 (18 %)	92 / 1213 (8 %)
Urban (indicator)	3868 / 5934 (65 %)	1770 / 3240 (55 %)	5036 / 7961 (63 %)	602 / 1213 (50 %)

[a] A CWS is considered exposed to wildfire if they have experienced at least one wildfire in their source watershed or up to five watersheds upstream in the period 1984 to 2022.
[b] Note that the total number of CWSs is now 9174. This is due to the integration of available WHP data, which results in losing 2 CWSs from our sample. Following documentation from the 2023 WHP dataset, a CWS's maximum WHP is classified as "High" if $339 \leq$ WHP ≤ 1565 and "Very High" WHP > 1565 (Scott et al., 2024).
[c] Mean (SD); n / N (%).

very high maximum WHP. The first row presents results for all CWSs while the second and third rows present results for surface water and groundwater CWSs, respectively. The differences reveal that systems that experienced wildfire burns have higher social vulnerability scores compared to systems that did not experience a burn. Similarly, CWSs that have high or very high WHP have higher social vulnerability scores, on average, across all four SVI themes as well as the overall index. This can be interpreted as evidence that populations served by CWSs that experience wildfire are, on average, more socially vulnerable, both overall and along multiple dimensions, compared to populations served by CWSs that do not experience wildfire. On average, there is a 10 percentile point difference in overall SVI between CWSs that have experienced an upstream wildfire burn and those that have not.

When we consider surface water and groundwater systems separately, the differences in mean CWS SVI values for systems that have and have not experienced wildfire are similar to the overall differences. This suggests that the correlation between CWS social vulnerability and wildfire exposure is not driven by large surface water systems with many source facilities that serve urban populations, which may be more diverse. Comparing mean CWS SVI values for surface water and groundwater CWS with and without high maximum WHP supports this notion as well. In fact, the differences in social vulnerability scores are more pronounced among groundwater systems with high or very high maximum WHP compared to surface water systems.

To better understand what drives these differences in vulnerability, we compare means for the individual variables used to calculate overall CWS SVI in Fig. 6.

The difference in vulnerability is most pronounced among indicators related to socioeconomic status, such as the percentage of the population below 150 % of the poverty level and the percentage of the population without a high school diploma, as well as indicators related to racial and ethnic minority status.[18] On average, CWSs that experienced a wildfire burn within the study period have a higher percentage of population with income below 150 % of the poverty level (+2.6 %) and a higher

[18] For the 2020 SVI calculations, the percentage of population that speaks English "less than well" was moved from the "Racial and Ethnic Minority Status" Theme to the "Household Characteristics" Theme. Here, we group them together although they belong to different SVI themes.

Table 3
Demographic and socioeconomic variables and definitions derived from 2015 to 2020 ACS estimates.

Variable name	Definition	SVI theme
Persons below Poverty (%)	Percentage of persons in a CWS service area below 150 % of the federal poverty line.	Socioeconomic Status
Unemployment Rate (%)	Percentage of unemployed civilians (age ≥ 16) in a CWS service area.	Socioeconomic Status
Cost-burned Occupied Housing Units (%)	Percentage of cost-burned occupied housing units with annual income less than $75,000 in a CWS service area. The denominator is the estimate of total housing units in a CWS service area.	Socioeconomic Status
No H.S. Diploma (%)	Percentage of persons (age ≥ 25) in a CWS service area with no high school diploma.	Socioeconomic Status
Uninsured Persons (%)	Percentage of uninsured persons in a CWS service area.	Socioeconomic Status
Persons Aged $\geq$65 (%)	Percentage of persons in a CWS service area aged 65 and older.	Household Characteristics
Persons aged $\leq$17 (%)	Percentage of persons in a CWS service area aged 17 and younger.	Household Characteristics
Persons with Disability (%)	Percentage of persons in a CWS service area with a disability.	Household Characteristics
Single Parent HH (%)	Percentage of single-parent households with children under 18 in a CWS service area.	Household Characteristics
English "Less than well" (%)	Percentage of persons (age ≥ 5) in a CWS service area who speak English "less than well".	Household Characteristics
Minorities (%)	Percentage of persons in a CWS service area that are a minority (Hispanic or Latino; Black and African American, Not Hispanic and Latino; American Indian and Alaska Native, Not Hispanic or Latino; Asian, Not Hispanic or Latino; Native Hawaiian and Other Pacific Islander, Not Hispanic or Latino; Two or More Races, Not Hispanic or Latino; Other Races, Not Hispanic or Latino).	Racial & Ethnic Minority Status
Housing >10 Units (%)	Percentage of housing in a CWS service area in structures with 10 or more units. The denominator is the estimate of total housing units in a CWS service area.	Housing Type & Transportation
Mobile Homes (%)	Percentage of mobile homes in a CWS service area. The denominator is the estimate of total housing units in a CWS service area.	Housing Type & Transportation
People > Rooms in HH (%)	Percentage of occupied housing units in a CWS service area with more people than rooms.	Housing Type & Transportation
No Vehicle (%)	Percentage of households within a CWS service area with no vehicle available.	Housing Type & Transportation
Persons in Group Quarters (%)	Percentage of persons in a CWS service area in group quarters (e.g., dormitories, correctional facilities, nursing homes).	Housing Type & Transportation
Urban[a]	Dummy variable = 1 if CWS service area is primarily within a "Metro" county (RUCC $\leq$3); = 0 otherwise.	NA

Definitions for SVI indicator variables are adapted from the CDC/ATSDR SVI documentation (CDC/ATSDR, 2022).
[a] "Urban" is not an SVI indicator variable and is instead derived from the 2023 Rural Urban Continuum Codes (RUCC).

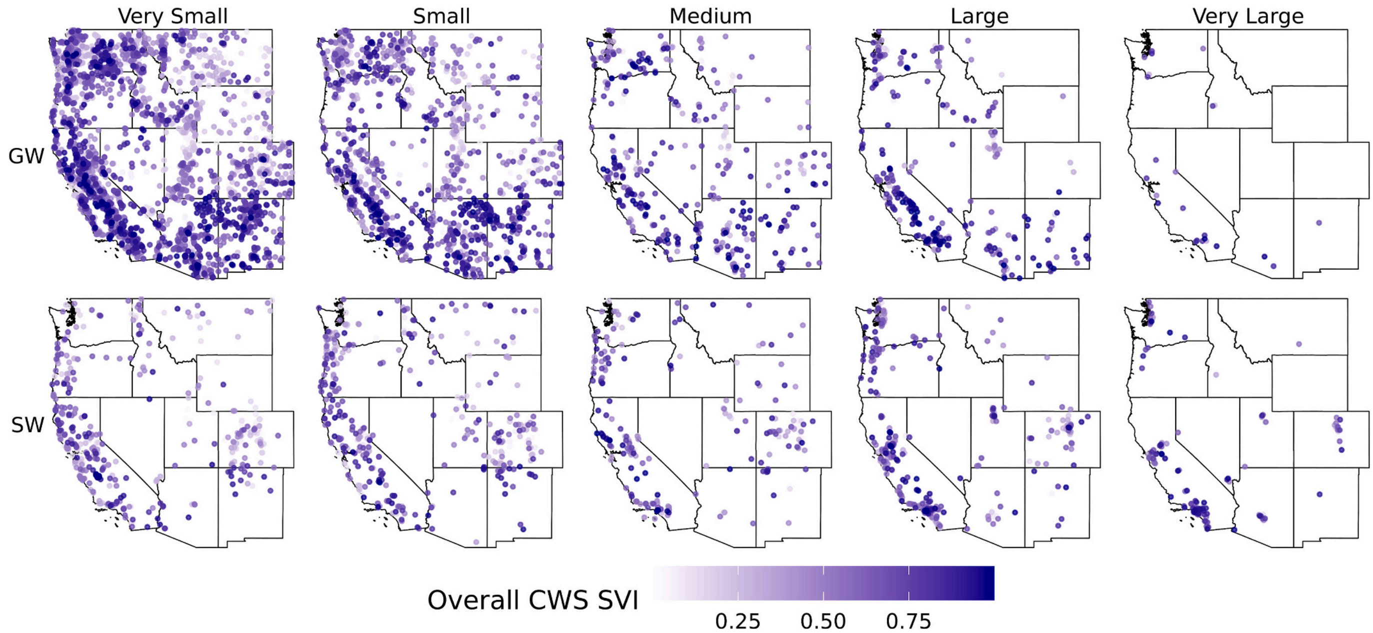

Fig. 4. Spatial distribution of CWSs by size and overall CWS SVI. The size categories refer to the population served with "Very Small" corresponding to 500 or less people served, "Small" corresponding to 501–3300 people served, "Medium" corresponding to 3301–10,000 people served, "Large" corresponding to 10,000–100,000 people served, and "Very Large" corresponding to 100,000+ people served.

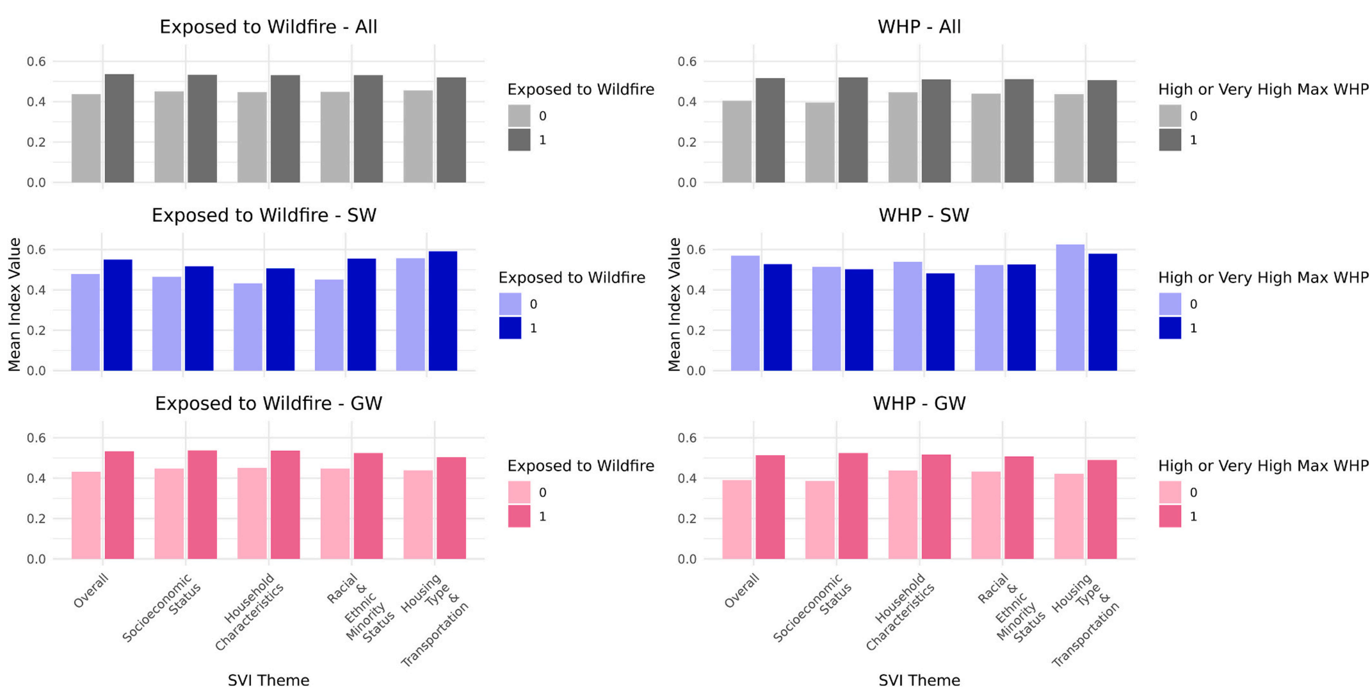

Fig. 5. Comparisons of overall CWS SVI and SVI theme mean values.

percentage of population without a high school diploma (+2.3 %). Additionally, CWSs that experienced a wildfire burn have a higher percentage of population that are racial and ethnic minorities (+5.9 %) compared to CWSs that have not experienced a wildfire burn. Considering WHP instead of exposure yields similar results.

The difference in means is least pronounced or nonexistent among indicators related to housing type and transportation. There is no significant difference in the mean percentage of population in housing structures with 10 or more units or in the mean percentage of households within a CWS service area with no vehicle available. Furthermore, the significant difference in means for indicators related to housing type and transportation are all <1 %, apart from the percentage of mobile homes in a CWS service area (+1.4 % for CWSs that have experienced a wildfire burn).

We visualize the relationship between wildfire exposure and social vulnerability in Fig. 7, which graphs the percentage of CWSs within each social vulnerability quartile exposed to wildfire by year. The percentage of high vulnerability CWSs exposed to wildfire is greater than that of less vulnerable CWSs in every year from 1984 to 2022. This finding is also true for medium-high vulnerability CWSs but is less pronounced, while the percentages of low-medium vulnerability CWSs and low vulnerability CWSs exposed to wildfire exhibit similar levels over time. Overall,

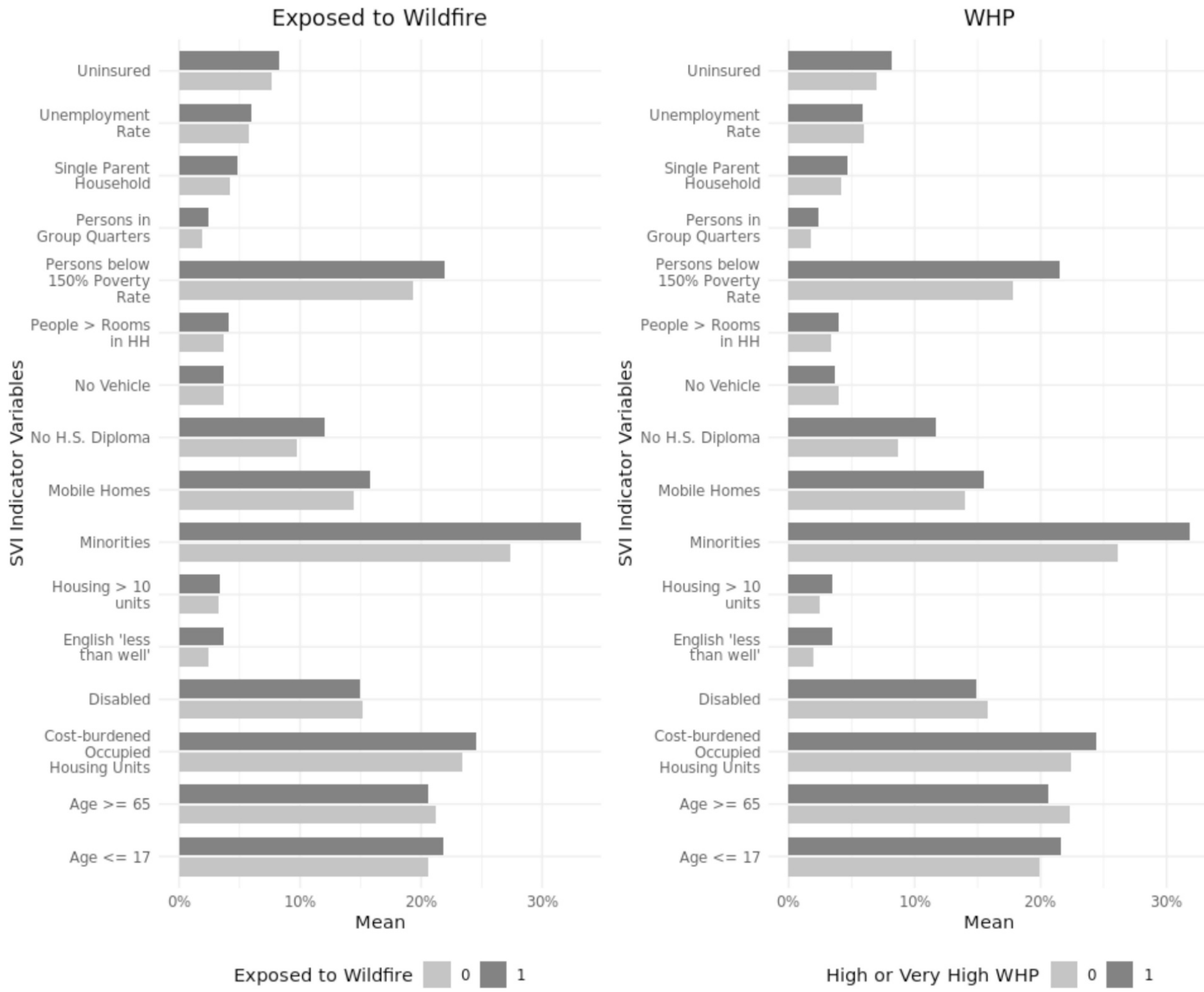

Fig. 6. Comparing means for individual SVI variables.

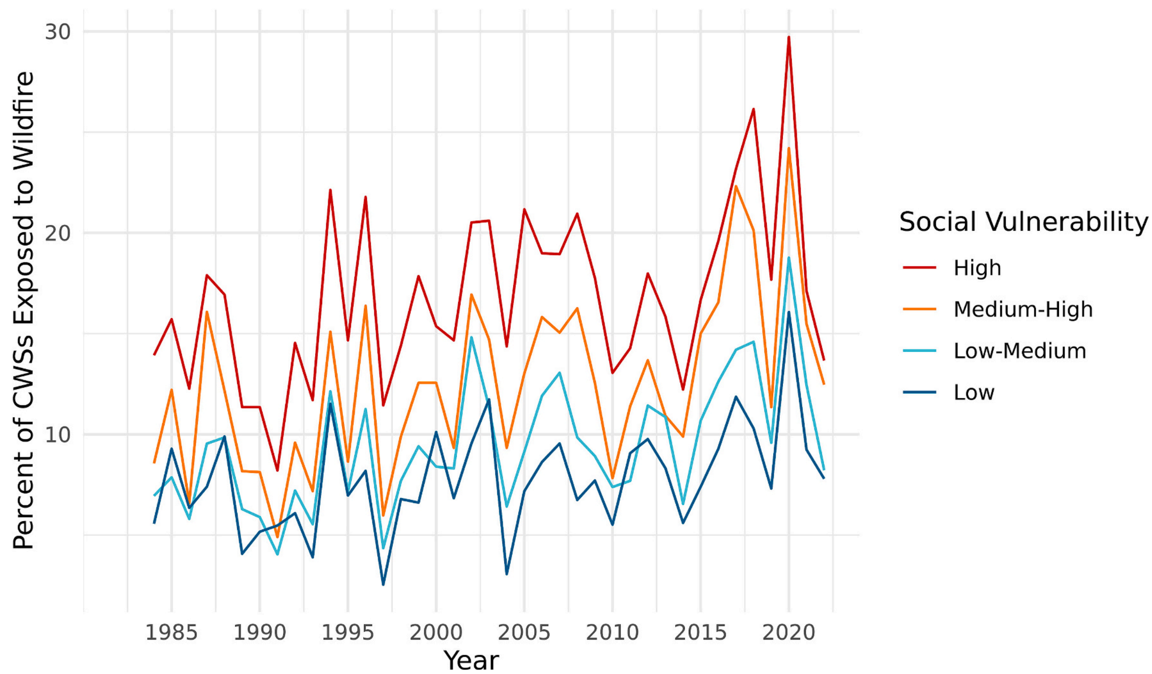

Fig. 7. Wildfire exposure over time by overall CWS SVI quartile.

Fig. 7 supports the finding that CWSs with relatively high social vulnerability were exposed more frequently to wildfire in their CWS's upstream source watershed.

3.2.2. Regression analyses of wildfire exposure and WHP

The independent variables of interest are the overall CWS SVI, the four CWS SVI themes, and the sixteen demographic variables that are used to construct the CWS SVI. The dependent variables of interest are whether or not a CWS experienced any upstream wildfire from 1984 to 2022 ($Wildfire_i$) and the log of the maximum WHP index in a CWS's upstream area ($\log(\max WHP_i)$). The primary regression model is specified by Eq. (1).

$$Dependent\_Variable_i = \beta_0 + \beta_1 SVI_i + \beta_2 urban_i + \beta_3 \gamma_i + u_i \quad (1)$$

In Eq. (1), $Dependent\_Variable_i$ represents either $Wildfire_i$, which is a dummy variable equal to one if a CWS experienced any burn in the upstream watershed area from 1984 to 2022, or $\log(\max WHP_i)$, which is the log of the maximum WHP index in a CWS's upstream area. SVI_i is the CWS SVI percentile rank for the service area corresponding to CWS i; $urban_i$ is a dummy variable indicating if the service area for CWS i is in an urban county; γ_i is a vector of CWS-level covariates including average daily population served and a dummy variable indicating if CWS i relies on surface water; u_i is the standard error term calculated by the Ordinary Least Squares (OLS) regression and is assumed to be normally distributed with mean zero. β_0 is the intercept estimated by the OLS regression while β_1,β_2,and β_3 are estimations of unknown parameters that describe the correlation between wildfire exposure or log(max WHP) (depending on the independent variable) and social vulnerability (either the overall CWS SVI, the CWS SVI themes, or the indicator variables), a binary variable indicating whether a CWS is located in an urban area (urban), and CWS-level covariates (average daily population served and a binary variable indicating whether a CWS relies primarily on SW), respectively.

Table 4 provides regression results for models with $Wildfire_i$ and $\log(\max WHP_i)$ as dependent variables. In Table 4 and the following regression tables, we include results for all systems, systems whose primary source is surface water, and systems whose primary source is groundwater for both specifications.

The coefficients on overall SVI percentile ranking and urban are positive and significant in all six regressions shown in Table 4. This means that an increase in overall SVI is associated with an increase in the probability that a CWS has experienced an upstream wildfire event. For example, a ten percentile point increase in overall CWS SVI (i.e., increasing from an overall CWS SVI of 0.70 to 0.80) is associated with an approximately 3 percentage point increase in the probability that a CWS has experienced an upstream wildfire event, holding all other variables constant. The results also suggest that populations with higher SVI percentile rankings are in areas with higher maximum WHP in their CWS's upstream source area. In columns (4) through (6), we can interpret the coefficients as the association between overall CWS SVI and maximum WHP. So, a ten percentile point increase in overall CWS SVI is associated with an approximately 9 % increase in maximum WHP, holding all other variables constant. Notably, comparing (1) to (2), the coefficient on overall SVI percentile ranking is 8.5 percentage points lower when we just consider surface water CWSs. The coefficient on urban is relatively similar across specifications, and the results from Table 4 imply that urban CWSs are 10–13 % more likely to have experienced an upstream wildfire event than rural CWSs. To investigate these results further, we regress $Wildfire_i$ and $\log(\max WHP_i)$ on CWS SVI theme percentile rankings and these results are shown in Table 5.

We find the coefficient on the socioeconomic status SVI percentile ranking is positive for all specifications, though when we consider only surface water CWS, we find lower levels of significance or non-significance. The coefficient on the household characteristics SVI percentile ranking is positive and significant for all specifications except for (5). The positive relationships between log(max WHP) and the socioeconomic status and household characteristic SVI themes appear to be driven largely by variation in the demographics of groundwater CWSs rather than surface water CWSs, given the coefficients for these themes reported in (5) which are not significantly different from zero at the 0.05 level. The coefficient on the racial and ethnic minority status SVI percentile ranking is positive and significant for surface water CWSs, (2) and (5), but not significantly different from zero for the groundwater CWSs, (3) and (6), indicating that the positive correlation between the racial and ethnic minority status SVI and wildfire exposure as well as WHP is driven primarily by outcomes for surface water CWSs. Again, the coefficient on urban is positive and significant for all specifications.

Lastly, in Table 6 we show the results when we consider additional heterogeneity in the relationship between social vulnerability and wildfire by regressing $Wildfire_i$ and $\log(\max WHP_i)$ on individual demographic and socioeconomic variables used to calculate the overall SVI and SVI theme percentile rankings.

The size and significance of the coefficient estimates in Table 6 are generally similar across specifications for both exposure to wildfire as the dependent variable as well as when log(max WHP) is the dependent variable. Notably, this pattern holds for the specifications using all CWSs and GW CWSs, with a few exceptions. The estimates for variables associated with the socioeconomic theme (persons below 150 % poverty rate, unemployment rate, cost-burdened housing units, no high school diploma, uninsured) vary the most between surface water and groundwater CWSs. Comparing the coefficient estimates for socioeconomic variables between these two groups shows that they differ in significance and sign. In (5) and (6), the coefficient estimates for the

Table 4
Regression results (overall SVI).

	Wildfire			Log(Max WHP)		
	All (1)	SW (2)	GW (3)	All (4)	SW (5)	GW (6)
Overall SVI	0.278***	0.193***	0.289***	0.912***	0.325**	1.015***
	(0.017)	(0.040)	(0.019)	(0.063)	(0.139)	(0.071)
Urban (indicator)	0.110***	0.130***	0.105***	0.561***	0.573***	0.556***
	(0.010)	(0.024)	(0.011)	(0.037)	(0.081)	(0.042)
Avg. Daily Population Served (1000s)	0.0001*	0.0001	0.001***	0.0002	0.0003	0.002
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.001)
SW (indicator)	0.074***			0.408***		
	(0.013)			(0.049)		
N	9174	1559	7615	9174	1559	7615
R^2	0.044	0.035	0.041	0.052	0.037	0.046

Standard deviations in parentheses.
* $p < .1$.
** $p < .5$.
*** $p < .01$.

Table 5
Regression results (SVI themes).

	Wildfire			Log(Max WHP)		
	All	SW	GW	All	SW	GW
	(1)	(2)	(3)	(4)	(5)	(6)
Socioeconomic status SVI	0.115***	0.032	0.135***	0.764***	0.358*	0.863***
	(0.023)	(0.053)	(0.026)	(0.087)	(0.184)	(0.098)
Household characteristics SVI	0.142***	0.159***	0.140***	0.281***	−0.028	0.350***
	(0.022)	(0.051)	(0.024)	(0.081)	(0.176)	(0.090)
Racial & ethnic minority status SVI	0.052**	0.167***	0.030	−0.007	0.458**	−0.107
	(0.021)	(0.052)	(0.023)	(0.078)	(0.180)	(0.087)
Housing type & transportation SVI	0.037*	−0.076	0.048**	0.015	−0.302*	0.048
	(0.021)	(0.050)	(0.023)	(0.077)	(0.171)	(0.087)
Urban (indicator)	0.108***	0.101***	0.105***	0.572***	0.497***	0.572***
	(0.011)	(0.026)	(0.012)	(0.039)	(0.091)	(0.043)
Avg. daily population served (1000s)	0.0001*	0.0001	0.001***	0.0004	0.0003	0.002
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.001)
SW (indicator)	0.081***			0.440***		
	(0.013)			(0.050)		
N	9174	1559	7615	9174	1559	7615
R^2	0.045	0.045	0.041	0.054	0.043	0.049

Standard deviations in parentheses.
* $p < .1$.
** $p < .5$.
*** $p < .01$.

percentage of persons below 150 % poverty rate and the percentage of cost-burdened occupied housing units are significant for both surface water and groundwater CWSs, but the coefficient estimates for the percentage of persons below 150 % poverty rate differ in sign. The coefficient estimates for variables associated with the other themes (household characteristics, racial and ethnic minority status, and housing and transportation) are more consistent across specifications. The coefficient estimates on the percentage of the population aged 65 and older, the percentage of the population identifying as a racial or ethnic minority, and the percentage of the population living in group quarters are positive and significant across all specifications. One exception is the coefficient estimate on the percentage of housing units that are mobile homes. The coefficient on mobile homes is negative and statistically significant for regressions with log(max WHP) as the dependent variable, whereas the coefficient is statistically significant and positive in (1) when considering all CWSs with exposure to wildfire as the dependent variable. Finally, the coefficient estimate on urban remains positive and significant for all specifications.

4. Discussion

Our results highlight correlations in the characteristics of CWSs and service populations exposed to wildfire as well as their landscape-based wildfire hazard potential. First, we find that the overall percentage of CWSs exposed to wildfire trends upward from 1984 to 2022. This trend holds when considering CWSs with primarily surface water and groundwater sources separately, although we find that surface water systems are more likely to have been exposed to wildfire. This may be particularly relevant because most people in the western U.S. rely on surface water sources and thus may be more vulnerable to wildfire impacts on source water.

Second, the analysis reveals that CWSs that have experienced wildfire events upstream are, on average, more socially vulnerable than CWSs that have not experienced wildfire upstream. Similarly, CWSs that have high or very high maximum WHP are, on average, more socially vulnerable than CWSs that do not have high or very high maximum WHP. These results hold when we analyze CWSs that primarily rely on surface water and groundwater separately, which suggests that the difference in social vulnerability is not entirely attributed to surface water systems serving large urban populations associated with more diverse communities. Additionally, when we regress the probability of experiencing at least one upstream wildfire event between 1984 and 2022 on social vulnerability indices and indicator variables, we obtain positive and significant coefficient estimates for the overall CWS SVI percentile ranking and the household characteristics SVI percentile ranking. These results hold when considering all CWSs, as well as when considering CWSs with primarily surface water and groundwater sources separately. In both the difference in means and regression analyses, we find that the relationship between wildfire exposure and the percentage of the CWS service population that is a racial or ethnic minority is positive and significant. We find similar results in our analysis looking at WHP, although there tends to be fewer statistically significant positive correlations between WHP and individual vulnerability variables, particularly for surface water CWSs.

Our results are similar to other studies analyzing correlations of social vulnerability with other environmental outcomes and hazards. Sanchez et al. (2023) show that in many parts of the U.S., areas with high social vulnerability overlap with areas that are vulnerable to shortages in surface water availability and estimate coefficients of a similar magnitude when regressing the probability of exposure to a water shortage on SVI indicator variables. Research by Tascon-Gonzalez et al. (2020) uses the SVI to evaluate community vulnerability to flood risks, while Palaiologou et al. (2019) evaluate social vulnerability to large wildfires in the western U.S. and find that communities with high vulnerability were disproportionately exposed to areas burned by wildfire. Several studies look at the correlations between sociodemographic variables and drinking water quality and find disparities, including elevated exposure to drinking water contaminants for minority groups (Austin et al., 2024; Balazs et al., 2011; Marcillo et al., 2021; Uche et al., 2021).

The factors that make a community resilient against the threats from wildfire to water supply—ability to protect against, mitigate, absorb, respond to, or recover—will differ substantially depending on various local and regional characteristics. We focus on analyzing the correlation between the characteristics of the populations served by CWSs and the occurrence of wildfire events and risk. Ultimately, community-level vulnerability to wildfire through drinking water systems will be determined by the actions and characteristics of the CWS in addition to the population that they serve. For example, larger and wealthier communities may have CWSs with multiple water intakes, more extensive water-quality testing, and more resources to draw on for system-level repairs and other post-fire investments. These attributes may lessen a community's vulnerability to the most extreme water-related costs associated with a wildfire event. For example, following Colorado's

Table 6
Regression results (SVI indicator variables).

	Wildfire			Log(Max WHP)		
	All (1)	SW (2)	GW (3)	All (4)	SW (5)	GW (6)
Persons below 150 % poverty rate (%)	0.004***	−0.001	0.005***	0.019***	−0.016***	0.024***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.006)	(0.003)
Unemployment rate (%)	−0.006***	−0.004	−0.006***	−0.029***	0.009	−0.032***
	(0.001)	(0.003)	(0.001)	(0.005)	(0.011)	(0.005)
Cost-burdened occupied housing units (%)	0.002**	0.007***	0.0004	0.022***	0.042***	0.018***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.003)
No high school diploma (%)	0.002	−0.001	0.003**	0.006	−0.012	0.011**
	(0.001)	(0.003)	(0.001)	(0.004)	(0.010)	(0.005)
Uninsured (%)	0.004***	−0.002	0.005***	0.010**	−0.012	0.013***
	(0.001)	(0.003)	(0.001)	(0.004)	(0.009)	(0.004)
Persons aged ≥ 65 (%)	0.009***	0.008***	0.009***	0.024***	0.015**	0.025***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.008)	(0.004)
Persons aged ≤ 17 (%)	0.012***	0.011***	0.012***	0.029***	0.008	0.032***
	(0.001)	(0.003)	(0.001)	(0.004)	(0.010)	(0.005)
Persons with disability (%)	−0.002**	−0.0001	−0.002**	−0.004	0.010	−0.004
	(0.001)	(0.003)	(0.001)	(0.004)	(0.010)	(0.005)
Single parent household (%)	0.004**	0.008*	0.003*	−0.015**	0.009	−0.017**
	(0.002)	(0.004)	(0.002)	(0.006)	(0.014)	(0.007)
English ‘less than well’ (%)	0.001	−0.001	0.001	0.004	−0.001	0.006
	(0.002)	(0.005)	(0.002)	(0.007)	(0.016)	(0.007)
Minorities (%)	0.001***	0.003***	0.001**	0.005***	0.011***	0.003*
	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.003)	(0.001)
Housing > 10 units (%)	0.0002	−0.004**	0.001	0.001	−0.018***	0.006
	(0.001)	(0.002)	(0.001)	(0.003)	(0.006)	(0.004)
Mobile homes (%)	0.001*	0.001	0.001	−0.005***	−0.012***	−0.004**
	(0.0004)	(0.001)	(0.0005)	(0.002)	(0.004)	(0.002)
People > rooms in household (%)	−0.011***	−0.006	−0.013***	−0.025***	0.014	−0.033***
	(0.002)	(0.004)	(0.002)	(0.006)	(0.013)	(0.006)
No vehicle (%)	−0.005***	−0.010**	−0.005***	−0.042***	−0.062***	−0.037***
	(0.002)	(0.004)	(0.002)	(0.006)	(0.013)	(0.006)
Persons in group quarters (%)	0.006***	0.006***	0.005***	0.013***	0.011*	0.013***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.006)	(0.003)
Urban (indicator)	0.127***	0.100***	0.129***	0.546***	0.319***	0.577***
	(0.011)	(0.028)	(0.012)	(0.041)	(0.094)	(0.045)
Avg. daily population served (1000s)	0.0002***	0.0002**	0.001***	0.001*	0.0004	0.003*
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.001)
SW (indicator)	0.105***			0.445***		
	(0.013)			(0.050)		
N	9174	1559	7615	9174	1559	7615
R^2	0.061	0.069	0.061	0.072	0.120	0.068

Standard deviations in parentheses.
* $p < .1$.
** $p < .5$.
*** $p < .01$.

Marshall Fire, the City of Superior, Colorado had the financial resources that enabled it to void all household utility bills for the month when the fire occurred (Whelton et al., 2023). Future research could explore how the physical infrastructure and financial well-being of CWSs interact with the characteristics of the populations that they serve to determine the vulnerability of communities to wildfire events that impact drinking water systems.

In conclusion, our analyses explore correlations but not causal relationships between CWS characteristics and service-area population demographics and wildfire exposure and landscape-based WHP. We leveraged data on water system-level characteristics, CWS service-area boundaries, social vulnerability, and large wildfire events to construct a CWS SVI that may be useful in the future to understand the social dimensions of vulnerability of CWSs to wildfire impacts on drinking water. This information may be utilized by future researchers or policymakers to contextualize information about populations served by CWSs facing increasing upstream wildfire risk.

Credit authorship contribution statement

Charlotte Wachter: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Jordan F. Suter:** Writing – review & editing, Supervision, Conceptualization. **Jesse Burkhardt:** Writing – review & editing, Supervision, Conceptualization. **Wes Austin:** Writing – review & editing, Data curation. **Beth M. Haley:** Writing – review & editing. **Siyu Pan:** Writing – review & editing. **Sonja H. Kolstoe:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

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Appendix

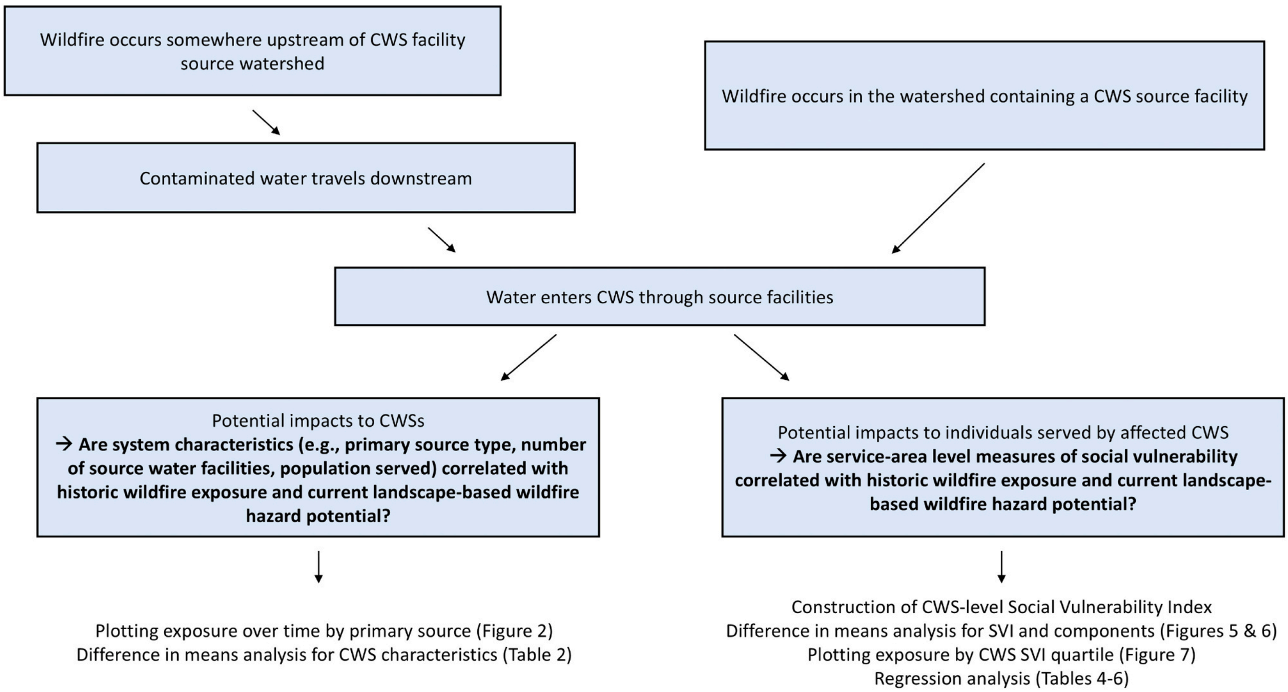

Fig. A1. A diagram depicting how community water systems and the populations they serve are exposed to wildfire, our research questions when examining community water system characteristics and service population demographics, and the analyses we use to explore these questions.

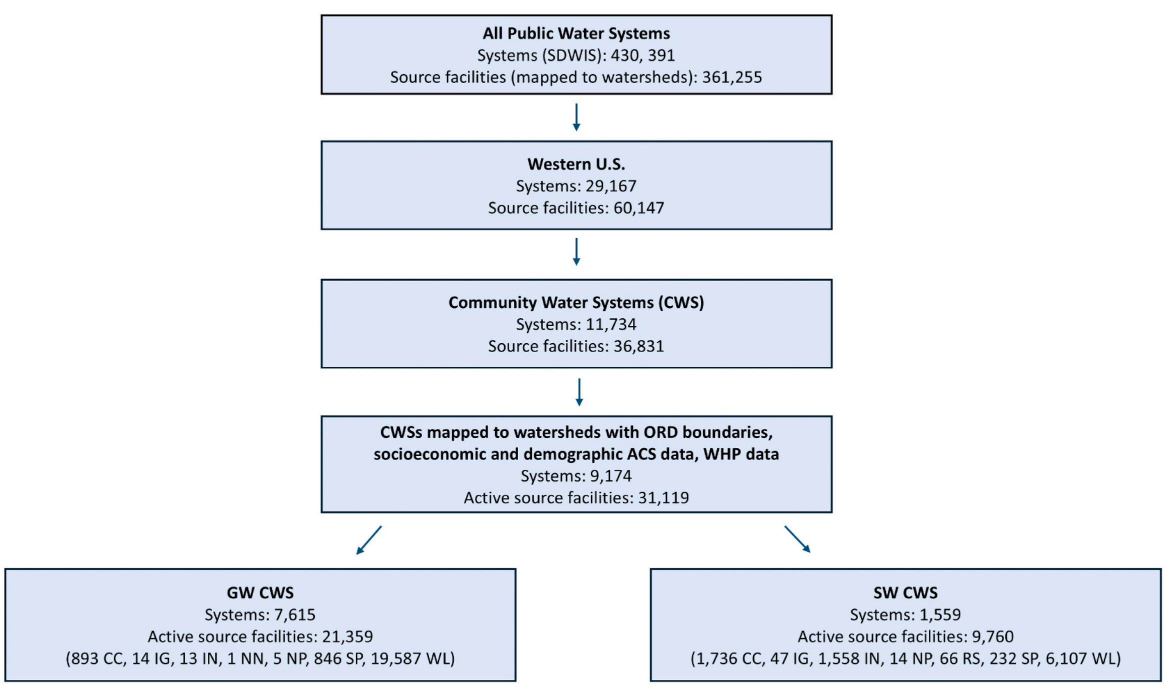

Fig. A2. Selection of relevant community water systems from the Safe Drinking Water Information System (SDWIS) database. Water source characterization is based on the SDWIS variable "GW_SW_CODE", which "identifies whether a system's water source is groundwater (GW) or surface water (SW) under SDWA." Definition from SDWIS Data Download Dictionary: https://echo.epa.gov/tools/data-downloads/sdwa-download-summary.

Data availability

Data will be made available on request.

References

Abatzoglou, J.T., Kolden, C.A., 2013. Relationships between climate and macroscale area burned in the western United States. Int. J. Wildland Fire 22 (7), 1003–1020.
Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proc. Natl. Acad. Sci. 113 (42), 11770–11775.
Allaire, M., Wu, H., Lall, U., 2018. National trends in drinking water quality violations. Proc. Natl. Acad. Sci. 115 (9), 2078–2083.
Austin, W., Bardot, T., El-Khattabi, A.R., 2024. Comparative Analysis of Service Area Boundaries and Disparities in Drinking Water Quality. *U.S. EPA National Center for Environmental Economics Working Paper Series*. Working Paper 24-07. https://www.epa.gov/system/files/documents/2024-09/2024-07.pdf.
Balazs, C., Morello-Frosch, R., Hubbard, A., Ray, I., 2011. Social disparities in nitrate contaminated drinking water in California's San Joaquin Valley. Environ. Health Perspect. 119 (9), 1272–1278. , June.
Bowman, D.M.J.S., Williamson, G.J., Abatzoglou, J.T., Kolden, C.A., Cochrane, M.A., Smith, A.M.S., 2017. Human exposure and sensitivity to globally extreme wildfire events. Nat. Ecol. Evol. 1 (3), 0058.
CDC. n.d. My Water's Fluoride Glossary, Definition Mixed Source. Available from: https://nccd.cdc.gov/doh_mwf/Help/MWFGlossary.aspx#:~:text=Mixed%20Source,%2C%20surface%2C%20or%20parent%20sources.
CDC/ATSDR. 2022. CDC/ATSDR SVI 2020 Documentation. Available from: https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2020.html.
Economic Research Service, United States Department of Agriculture. 2024. Rural-Urban Continuum Codes. Available from: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/.
Emelko, M.B., Silins, U., Bladon, K.D., Stone, M., 2011. Implications of land disturbance on drinking water treatability in a changing climate: Demonstrating the need for "source water supply and protection" strategies. Water Res. 45 (2), 461–472.
Flanagan, B.E., Gregory, E.W., Hallisey, E.J., Heitgerd, J.L., Lewis, B., 2011. A social vulnerability index for disaster management. Journal of Homeland Security and Emergency Management 8 (1), 0000102202154773551792.
Flanagan, B.E., Hallisey, E.J., Adams, E., Lavery, A., 2018. Measuring community vulnerability to natural and anthropogenic hazards: the Centers for Disease Control and Prevention's Social Vulnerability Index. J. Environ. Health 80 (10), 34–36.
Flannigan, M., Cantin, A.S., de Groot, W.J., Wotton, M., Newbery, A., Gowman, L.M., 2013. Global wildland fire season severity in the 21st century. For. Ecol. Manag. 294 (S1), 54–61.
Gao, P., Terando, A.J., Kupfer, J.A., Varner, J.M., Stambaugh, M.C., Lei, T.L., Hiers, J.K., 2021. Robust projections of future fire probability for the conterminous United States. Sci. Total Environ. 789, 13.
Hallema, D.W., Robinne, F.-N., Bladon, K.D., 2018a. Reframing the challenge of global wildfire threats to water supplies. Earth's Future 6 (6), 772–776.
Hallema, D.W., Sun, G., Caldwell, P.V., Norman, S.P., Cohen, E.C., Liu, Y., Bladon, K.D., McNulty, S.G., 2018b. Burned forests impact water supplies. Nat. Commun. 9, 1307.
Hohner, A., Webster, J., Cawley, K., Rosario-Ortiz, F.L., Becker, W., 2018. Wildfire impacts on drinking water treatment process performance: Development of evaluation protocols and management practices, The Water Research Foundation, Denver, CO.
Hohner, A.K., Rhoades, C.C., Wilkerson, P., Rosario-Ortiz, F.L., 2019. Wildfires alter forest watersheds and threaten drinking water quality. Acc. Chem. Res. 52 (5), 1234–1244.
Kinoshita, A.M., Chin, A., Simon, G.L., Briles, C., Hogue, T.S., O'Dowd, A.P., Gerlak, A.K., Albornoz, A.U., 2016. Wildfire, water, and society: Toward integrative research in the "Anthropocene". Anthropocene 16, 16–27.
Mack, E., Lilja, R., Claggett, S., Sun, G., Caldwell, P., 2022. Forests to Faucets 2.0: Connecting Forests, Water, and Communities. Gen. Tech. Rep. WO-99,, 99. US Department of Agriculture, Forest Service, Washington Office, pp. 1–35.
Marcillo, C., Krometis, L.A., Krometis, J., 2021. Approximating community water system service areas to explore the demographics of SDWA compliance in Virginia. Int. J. Environ. Res. Public Health 18 (24), 13254. Number: 24 Publisher: Multidisciplinary Digital Publishing Institute.
Martin, D.A., 2016. At the nexus of fire, water and society. Philos. Trans. R. Soc. B 371 (1696), 20150172.
Moritz, M.A., Parisien, M.A., Batllori, E., Krawchuk, M.A., Van Dorn, J., Ganz, D.J., Hayhoe, K., 2012. Climate change and disruptions to global fire activity. Ecosphere 3 (6), 1–22.
[dataset] MTBS Direct Download: Burned Areas Boundaries Dataset., 2022. Monitoring Trends in Burn Severity (MTBS) Project. U.S. Forest Service/U.S, Geological Survey. Available online: https://mtbs.gov/direct-download.
Painter, M.A., Shah, S.H., Damestoit, G.C., Khalid, F., Prudencio, W., Chisty, M.A., Tormos-Aponte, F., Wilhelmi, W., 2024. A systematic scoping review of the Social Vulnerability Index as applied to natural hazards. Nat. Hazards 1–92.
Palaiologou, P., Ager, A.A., Nielsen-Pincus, M., Evers, C.R., Day, M.A., 2019. Social vulnerability to large wildfires in the western USA. Landsc. Urban Plan. 189, 99–116.
Paul, M.J., LeDuc, S.D., Lassiter, M.G., Moorhead, L.C., Noyes, P.D., Leibowitz, S.G., 2022. Wildfire induces changes in receiving waters: A review with considerations for water quality management. Water Resour. Res. 58 (9), e2021WR030699.
Pennino, M.J., Leibowitz, S.G., Compton, J.E., Beyene, M.T., LeDuc, S.D., 2022. Wildfires can increase regulated nitrate, arsenic, and disinfection byproduct violations and concentrations in public drinking water supplies. Sci. Total Environ. 804, 149890.
Pozo, D., Olrno, F.J., Alados-Arboledas, L., 1997. Fire detection and growth monitoring using a multitemporal technique on AVHRR mid-infrared and thermal channels. Remote Sens. Environ. 60 (2), 111–120.
Price, J.I., Heberling, M.T., 2018. The effects of source water quality on drinking water treatment costs: a review and synthesis of empirical literature. Ecol. Econ. 151, 195–209.
Price, J.I., Renzetti, S., Dupont, D., Adamowicz, W., Emelko, M.B., 2017. Production costs, inefficiency, and source water quality: A stochastic cost frontier analysis of Canadian water utilities. Land Econ. 93, 1–11.
Proctor, C.R., Lee, J., Yu, D., Shah, A.D., Whelton, A.J., 2020. Wildfire caused widespread drinking water distribution network contamination. AWWA Water Science 2 (4), e1183.
R Core Team, 2024. R: a language and environment for statistical computing [Internet]. R Foundation for Statistical Computing, Vienna (Austria). Available from: https://www.R-project.org/.
Reilly, M.J., Dunn, C.J., Meigs, G.W., Spies, T.A., Kennedy, R.E., Bailey, J.D., Briggs, K., 2017. Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985–2010). Ecosphere 8 (3), e01695.
Rhoades, C.C., Nunes, J.P., Silins, U., Doerr, S.H., 2019. The influence of wildfire on water quality and watershed processes: new insights and remaining challenges. Int. J. Wildland Fire 28 (10), 721–725.
Robinne, F.-N., Bladon, K.D., Miller, C., Parisien, M.-A., Mathieu, J., Flannigan, M.D., 2018. A spatial evaluation of global wildfire-water risks to human and natural systems. Sci. Total Environ. 610-611, 1193–1206.
Robinne, F.-N., Hallema, D.W., Bladon, K.D., Flannigan, M.D., Boisramé, G., Bréthaut, C. M., Doerr, S.H., Di Baldassarre, G., Gallagher, L., Hohner, A.K., Khan, S.J., Kinoshita, A.M., Mordecai, R., Nunes, J.P., Nyman, P., Santin, C., Sheridan, G., Stoof, C.R., Thompson, M.P., Waddington, J.M., Wei, Y., 2021. Scientists' warning on extreme wildfire risks to water supply. Hydrol. Process. 35 (5), e14086.
Rust, A.J., Saxe, S., McCray, J., Rhoades, C.C., Hogue, T.S., 2019. Evaluating the factors responsible for post-fire water quality response in forests of the western USA. Int. J. Wildland Fire 28 (10), 769–784.
Sanchez, L., Warziniack, T., Knowles, M., 2023. The inequitable exposure of socially vulnerable groups to water shortages across the United States. Environ. Res. Lett. 18 (4), 044022.
Scanlon, B.R., Reedy, R.C., Fakhreddine, S., Yang, Q., Pierce, G., 2023. Drinking water quality and social vulnerability linkages at the system level in the United States. Environ. Res. Lett. 18 (9), 094039.
Schoennagel, T., Balch, J.K., Brenkert-Smith, H., Dennison, P.E., Harvey, B.J., Krawchuk, M.A., Mietkiewicz, N., Morgan, P., Moritz, M.A., Rasker, R., Turner, M.G., Whitlock, C., 2017. Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences*. U.S.A. 114 (8), 4582–4590.
Scott, Joe H., Dillon, Gregory K., Jaffe, Melissa R., Vogler, Kevin C., Olszewski, Julia H., Callahan, Michael N., Karau, Eva C., Lazarz, Mitchell T., Short, Karen C., Riley, Karin L., Finney, Mark A., Grenfell, Isaac C., 2024. Wildfire Risk to Communities: Spatial datasets of landscape-wide wildfire risk components for the United States, 2nd edition. Forest Service Research Data Archive, Fort Collins, CO. https://doi.org/10.2737/RDS-2020-0016-2.
Senande-Rivera, M., Insua-Costa, D., Miguez-Macho, G., 2022. Spatial and temporal expansion of global wildland fire activity in response to climate change. Nat. Commun. 13 (1), 1208.
Sjoberg, D., Whiting, K., Curry, M., Lavery, J., Larmarange, J., 2021. Reproducible Summary Tables with the gtsummary Package. R J. 13, 570–580. https://doi.org/10.32614/RJ-2021-053.
Sommerfeld, A., Senf, C., Buma, B., D'Amato, A.W., Després, T., Díaz-Hormazábal, I., Fraver, S., Frelich, L.E., Gutiérrez, Á.G., Hart, S.J., Harvey, B.J., He, H.S., Hlásny, T., Holz, A., Kitzberger, T., Kulakowski, D., Lindenmayer, D., Mori, A.S., Müller, J., Paritsis, J., Perry, G.L.W., Stephens, S.L., Svoboda, M., Turner, M.G., Veblen, T.T., Seidl, R., 2018. Patterns and drivers of recent disturbances across the temperate forest biome. Nat. Commun. 9, 2833.
Stevens-Rumann, C.S., Kemp, K.B., Higuera, P.E., Harvey, B.J., Rother, M.T., Donato, D. C., Morgan, P., Veblen, T.T., 2018. Evidence for declining forest resilience to wildfires under climate change. Ecol. Lett. 21 (2), 243–252.
Tanellari, E., Bosch, D., Boyle, K., Mykerezi, E., 2015. On consumers' attitudes and willingness to pay for improved drinking water quality and infrastructure. Water Resour. Res. 51 (1), 47–57.
Tascon-Gonzalez, L., Ferrer-Julia, M., Ruiz, M., Garcia-Melendez, E., 2020. Social vulnerability assessment for flood risk analysis. Water 12 (2), 558.
U.S. Census Bureau. 2020. American Community Survey 2016-2020 5-year Estimate. https://data.census.gov/.
U.S. EPA, 2024a. Drinking Water Data Downloads. https://echo.epa.gov/tools/data-downloads.
U.S. EPA, 2024b. Community water system service areas documentation. National Center for Environmental Economics Working Paper 24-07. Available at: https://www.epa.gov/system/files/documents/2024-10/2024-07_gs.pdf.
U.S. EPA., 2025a. Drinking Water Mapping Application to Protect Source Waters (DWMAPS). https://www.epa.gov/sourcewaterprotection/drinking-water-mapping-application-protect-source-waters-dwmaps.
U.S. EPA, 2025b. SDWA data download summary and data element dictionary. U.S. Environmental Protection Agency, Washington (DC). Available from: https://echo.epa.gov/tools/data-downloads/sdwa-download-summary.

U.S. Forest Service, Fire Modeling Institute, 2024. Wildfire Hazard Potential (WHP) Dataset. Missoula Fire Sciences Laboratory. Available at: https://research.fs.usda.gov/firelab/products/dataandtools/datasets/wildfire-hazard-potential.

U.S. Geological Survey, 2025. Watershed Boundary Dataset (WBD) [Internet]. U.S. Geological Survey, Reston (VA). Available from: https://www.usgs.gov/national-hydrography/watershed-boundary-dataset.

U.S. Geological Survey and U.S. Department of Agriculture, Natural Resources Conservation Service. 2012. Federal Standards and Procedures for the National Watershed Boundary Dataset (WBD) (3d ed.): U.S. Geological Survey Techniques and Methods 11–A3, 63 p. Available on the World Wide Web at http://pubs.usgs.gov/tm/tm11a3/.

Uche, U.I., Evans, S., Rundquist, S., Campbell, C., Naidenko, O.V., 2021. Community-level analysis of drinking water data highlights the importance of drinking water metrics for the state, federal environmental health justice priorities in the United States. Int. J. Environ. Res. Public Health 18 (19), 10401.

Um, M.J., Kwak, S.J., Kim, T.Y., 2002. Estimating willingness to pay for improved drinking water quality using averting behavior method with perception measure. Environ. Resour. Econ. 21, 285–300.

Wear, D.N., Warziniack, T., O'Dea, C., Coulston, J., 2024. Changing Hazards, Exposure, and Vulnerability in the Conterminous United States. *Resources for the Future Working Paper Series.* 24-1. Available at https://media.rff.org/documents/WP_24-21.pdf.

Westerling, A.L., 2016. Increasing Western US Forest Wildfire Activity: sensitivity to changes in the timing of spring. Philos. Trans. R. Soc. B 371, 20150178.

Whelton, A.J., Seidel, C., Wham, B.P., Fischer, E.C., Isaacson, K., Jankowski, C., MacArthur, N., McKenna, E., Ley, C., 2023. The Marshall Fire: Scientific and policy needs for water system disaster response. AWWA Water Science 5 (1), e1318.

Wickham, H., Chang, W., Henry, L., Pedersen, T.L., Takahashi, K., Wilke, C., Woo, K., Yutani, H., Dunnington, D., van den Brand, T., 2025. ggplot2: Create elegant data visualisations using the grammar of graphics [Internet]. Version 3.5.2. R Foundation for Statistical Computing, Vienna (Austria). Available from: https://ggplot2.tidyverse.org.

Yang, S., Huang, Q., Yu, M., 2024. Advancements in remote sensing for active fire detection: A review of datasets and methods. Sci. Total Environ. 173273.