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Comparative Analysis of Service Area Boundaries and Disparities in Drinking Water Quality*

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Abstract

Service area boundaries are the geographic delineation of a drinking water system's customer base. A lack of precise service area boundaries may introduce errors in how measures of water quality are geospatially assigned in academic or regulatory work, potentially hindering our ability to locate and accurately characterize environmental justice concerns in drinking water. Many advances have been made in the collection and modelling of service areas, but there has been minimal systematic testing of the implications of employing distinct service area boundary types in the published literature. While it is generally understood that more accurate service area assignment methods will improve the precision of environmental justice analyses of drinking water quality, it is unclear how various assignment methods would impact the conclusions of empirical analyses or the potential magnitude of bias. This paper aims to fill this gap by summarizing a set of relatively novel environmental justice indicators in drinking water across all known service area assignment methods. We explore drinking water quality measures for arsenic, bacterial detection, disinfection byproduct formation, lead, nitrates, PFAS, and health-based violations of the Safe Drinking Water Act. We summarize each drinking water quality metric across service area assignment methods including the use of county served, zip codes served, the EPIC/SimpleLab dataset, boundaries created by the U.S. Geologic Survey, and a national data layer produced by EPA's Office of Research and Development. We find disparities in drinking water quality with respect to every drinking water quality metric included in this analysis, and we find that conclusions regarding the presence of a disparity depend on the service area boundary selected for at least one group of environmental justice concern for each drinking water quality measure. This paper helps to motivate the importance of collecting service areas as well as producing and maintaining a high-quality nationally consistent geodatabase of drinking water system service areas.

Keywords: Drinking Water, Safe Drinking Water Act, Service Area Boundaries, Environmental Justice
JEL: Q25, Q53, Q58, Y1

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1 Introduction

Drinking water systems across the U.S. face significant stressors that challenge their ability to provide households with clean and affordable drinking water (EPA, 2023a). In each year from 1982-2015, between 3-10% of drinking water systems, serving 9 to 45 million Americans, had a health-based violation of the Safe Drinking Water Act (SDWA) (Allaire et al., 2018). Prior audits of available SDWA violations data suggest there is also significant under-reporting of these violations (GAO, 2011). Communities with heightened vulnerability or social disadvantage are more likely to lack access to safe public drinking water, raising environmental justice concerns (Switzer and Teodoro, 2017; Pullen-Fedinick et al., 2019). These environmental justice concerns are increasingly important to federal policy analysis, state planning, state and federal decisions on where to allocate funding, academic research, and community advocacy efforts.

Conducting environmental justice analyses of access to safe and affordable drinking water quality requires accurate information on demographic groups in the defined areas of interest (i.e., service area boundaries). Though it is generally understood that more accurate service area assignment methods will improve the precision of environmental justice analyses of drinking water quality, it is unclear how various assignment methods would impact the conclusions of empirical analyses or the potential magnitude of bias. Prior analyses have predominantly relied on coarse approximations of water system service areas such as county or zip code served. While these representations are the simplest geospatial data to operationalize in an analysis, their use could bias analytic conclusions given the importance of accurately characterizing demographics within affected communities. In part due to data limitations, relatively few studies have compared the results of an environmental justice analysis across coarser and the more-refined service area boundary data. However, such comparisons are now possible with advances in the collection and modelling of service area boundaries both at the state and national level (Buchwald et al., 2022; Hydroshare, 2022; EPA, 2024b).[1] To our knowledge, no prior studies have conducted a nationwide environmental justice analysis comparing analytic conclusions according to coarse service area boundary approximations like counties to newer and more precise boundary representations. Moreover, no prior work has compared conclusions across all of the most recent nationwide service area boundary datasets. Characterizing this uncertainty will help analysts better understand the implications of decisions on how to delineate water system service area boundaries.

In this paper, we explore three research questions on the implications of water system service area delineation while also shedding light on the environmental justice dimension of drinking water quality. First, we summarize variation in drinking water quality at the national level across seven drinking water quality metrics and for different economic and demographic groups. Second, we investigate the extent to

[1] McDonald et al. (2022) and EPA (2024a) summarize and review data quality of all publicly-available state-level service area boundary data.

which the choice of how to delineate service area boundaries may yield different results in environmental justice analyses using a set of disparity measures, bivariate maps, and regression-based tests of statistical significance. Finally, we provide an array of supplemental analyses that offer explanations for why different service area representations can lead to different conclusions. We also conduct case studies highlighting the usefulness of geospatially-refined service area boundaries for accurately characterizing local hotspots of environmental justice concern or cumulative burden to other sources of pollution exposure (e.g., air pollution). We do not test the accuracy of any particular underlying service boundary or modelling methods and leave this investigation to other research, instead focusing on the extent to which conclusions on environmental justice disparities vary when adopting different service area boundary methods.

To answer our research questions, we start by assembling all existing service area boundary representations. These include county served identifiers from the Safe Drinking Water Inventory System (SDWIS),[2] zip codes served from SDWIS and multiple rounds of the Unregulated Contaminant Monitoring Rule data,[3] boundaries produced by the Environmental Policy Innovation Center (EPIC) and SimpleLab (Hydroshare, 2022), boundaries produced by USGS (Buchwald et al., 2022), and service areas generated by EPA (2024b). For each service area boundary type, we perform an areal apportionment over census block groups to determine the demographic composition of each water system.[4] We then combine demographic percentages for each water system with information on the total population served to derive the population of all demographic groups served by each water system.

Next, we construct seven national drinking water quality metrics relating to arsenic, bacterial contamination, disinfection byproducts, lead, nitrates, PFAS, and health-based violations of the Safe Drinking Water Act. We draw on over 20 million drinking water samples across several underlying datasets to produce these metrics (EPA, 2016a, 2022).[5] We then estimate demographic-specific and population-weighted average drinking water measures according to every service area boundary type. These average drinking water quality measures for each demographic group allow us to compute disparity measures reflecting heightened potential risks for groups of environmental justice concern. Equipped with these disparity measures, we compare the range of conclusions an analyst might encounter when employing distinct service area assignment methods. To better understand raw differences in population exposures to each drinking water quality concern, we characterize geographic variation using national maps, including bivariate maps that specifically highlight potential hotspots of environmental justice concern. We supplement these analyses with regression-based

[2]https://echo.epa.gov/tools/data-downloads

[3]https://www.epa.gov/dwucmr/occurrence-data-unregulated-contaminant-monitoring-rule

[4]For areal apportionment, we adopt the methods of EJSCREENbatch R package version 2.0, which makes use of population raster data to more accurately account for where populations live within census block groups.

[5]We source all Six Year Review data from a pre-collated collection of these records published online by Environmental Impact Data Collaborative (2023).

tests of whether disparities are statistically significant when controlling for water system characteristics such as population served and source water. We conclude with supplemental analyses, local case studies, sensitivity tests, and a discussion of limitations.

We find evidence of disparities in drinking water quality for every metric included in this analysis. We also find that the choice of service area boundary assignment method affects conclusions regarding the presence of disparity for all drinking water quality metrics with respect to at least one population group of environmental justice concern. The direction and magnitude of bias is not consistent across service area boundary types or drinking water quality indicators, suggesting that it is not generally possible to predict when the conclusions of an environmental justice analysis may differ depending on the type of service area boundary employed. We observe some of the greatest water quality disparities with respect to American Indian populations, who on average are served by drinking water systems with 2 - 3 times more health-based violations than those serving non-Hispanic White individuals from 2015-2023. This result is consistent across all boundary types, although the magnitude of the disparity is greatest for more geospatially precise boundaries such as the EPIC or EPA ORD data. We also find that Black populations experience greater drinking water quality concerns than non-Hispanic White populations across all drinking water indicators except arsenic and nitrates, and that these results are consistent across service area boundary representations. When characterizing disparities for low-income individuals (i.e., those with income less than twice the federal poverty limit), we find that these populations have elevated health-based violations, disinfection byproduct concentrations, and arsenic concentrations in comparison to populations with income above twice the federal poverty limit. A complete characterization of disparities, including with bivariate maps and regression tests of significance, is described in Section 5.

Our paper contributes to the literature on disparities in drinking water quality across many disciplines including geography, economics, sociology, and demography. Our paper is closely related to Mohai and Saha (2006) and Statman-Weil et al. (2020), speaking to a broader line of research on how geospatial techniques affect the results of an environmental justice analysis. By assessing the implications of using different service area boundary representations when conducting environmental justice analysis, our contributions are threefold. First, the scope of our analysis is national whereas previous analyses generally conduct regional or state-level analysis. Second, we expand the types of drinking water quality metrics beyond the set of information traditionally used for this purpose. Similarly, we investigate the potential for environmental justice concerns across more indicators of socioeconomic and environmental vulnerability than have been incorporated into prior work. Third, we explore why geospatial methods lead to different conclusions, providing evidence that may be relevant to other analytic contexts where coarse geographic approximations are used. Our focus on the extent to which the choice of geographic boundaries affects conclusions of an environmental justice analysis points to the importance of collecting and disseminating more accurate service area boundaries as well as to the value in using the highest-quality boundaries where possible in academic or regulatory analysis.

2 Background

In this section, we describe the role of water system service areas in federal regulatory environmental justice analyses, and we overview the academic literature relating to environmental justice concerns in drinking water. We detail how service areas have been used in these prior studies. The purpose of this section is to provide a rationale for our research questions and to situate this work within the broader multi-disciplinary literature on environmental justice and drinking water quality.

Since 1994, all significant U.S. federal rule-making efforts have been required to identify and address "disproportionately high and adverse human health or environmental effects" that may result from the action according to Executive Order 12898 (Clinton, 1994). More recent executive orders, such as EO 14096, have re-affirmed the commitment to identify environmental justice concerns using high-quality data and scientific research (Biden, 2023) As such, regulatory impact assessments for major new rules often include a qualitative discussion or quantitative analysis of environmental justice (Cecot and Hahn, 2022; Wolverton, 2023). Among other goals, these analyses aim to characterize baseline exposures to an environmental harm across demographic groups with varying levels of socioeconomic vulnerability. Where data and methods allow, these analyses may also assess how regulation would change baseline exposures to the environmental harms that are relevant to the regulation.[6]

In the context of drinking water, it is necessary to know the demographics of populations served by drinking water systems to determine whether any particular group may be experiencing disparate health or environmental impacts. Determining the socioeconomic characteristics of a drinking water system requires computing demographics based on the census geographical units overlapping a service area or, alternatively, imputing demographics based on simplifying assumptions with respect to the location of the service area. EPA's nationwide environmental justice analyses have traditionally assigned the demographic information of a county served to the drinking water system. County demographic imputation has been by far the most common practice; it was used in the environmental justice analysis of the 2020 Steam Electric Effluent Limitation Guidelines and the distributional analysis of household benefits and costs in the PFAS National Primary Drinking Water Regulation.[7] This method implicitly assumes that the demographics of a water

[6] See EPA (2016b) for more in depth discussion of the goals and methods of an environmental justice quantitative analysis for regulatory impact assessment.

[7] See chapter 14 of EPA (2020a) and section 8.3 of EPA (2024c)

system are the same as the primary county that is served by the water system.

Recent regulatory analyses have estimated water system demographics using more accurate representations of water system service areas when characterizing baseline conditions or policy scenarios. For example, the EJ analysis for the 2023 Steam Electric Effluent Limitation Guidelines used a combination of county and zip codes served to determine socioeconomic characteristics of drinking water systems (EPA, 2023c). The environmental justice exposures analysis for the PFAS drinking water rule used a combination of pre-delineated service areas produced by states in addition to zip codes where available (EPA, 2024c), although as mentioned county demographic shares were used for the cost and benefit distributional portion of the analysis. These analyses have employed greater geospatial specificity in service boundary assignment based on the assumption that such accuracy increases the ability to detect environmental justice concerns (Baden et al., 2007). However, the selection of service area boundary type has proceeded in a vacuum of evidence regarding the implications of different service area boundary assignment methods.

In the academic literature, many studies have evaluated how geographic assumptions affect the results of an environmental justice analysis. For example, Mohai and Saha (2006) describe how various metrics for estimating proximity to hazardous waste sites mis-characterize environmental justice concerns. However, due to data limitations, there has been relatively little exploration of how the choice of community water system boundary representation affects environmental justice analyses in the context of drinking water provision.

Most studies on environmental justice in drinking water have focused on states with available water system geospatial data, such as California and Texas. For example, Balazs et al. (2011) analyze the relationship between nitrate concentrations in community water systems (CWS) and the socio-demographic composition of their customers in the San Joaquin Valley of California. The authors find a positive but non-significant relationship between the percent Latino and a water system's estimated nitrate concentration. The authors estimate the demographic composition of the population potentially exposed to higher nitrate levels by intersecting spatial coordinates of water system facilities (e.g., public water supply wells) with census block groups. In contrast, Marcillo et al. (2021) use zip code served representations of service area boundaries to study environmental justice implications of health-based SDWA violations among community water systems in Virginia. The authors find that the proportion of Black individuals served by a water system is positively associated with more health-based violations. Notably, many public water systems were omitted from the final dataset due to systems not being georeferenced to zip codes. Other researchers have used zip code tabulation areas (ZCTAs) from the US Census Bureau to explore racial disparities in drinking water violations in California (Allaire and Acquah, 2022). Finally, some analyses use publicly-available service area boundary data directly. For example, Uche et al. (2021) use contaminant occurrence data and state-provided service area boundaries from California and Texas, finding that cumulative cancer risk from drinking water contaminants is greater in systems with higher shares of of Hispanic and Black individuals. The authors identify the demographic composition of each CWS by matching census tracts to water system boundaries and weighting by the percentage overlap between the CWS and intersecting census divisions. We found a single analysis that compares environmental justice conclusions across different methods for approximating populations served by a community water systems. Focusing on Pennsylvania, Statman-Weil et al. (2020) conduct a cross-method spatial analysis comparing areal weighting, dasymetric mapping, areal interpolation, and county-level analysis. The authors find that the methods used to determine service water boundaries affect the results of some statistical analyses, although their overall findings suggest no evidence of health-based SDWA violation disparities across racial groups or socio-economic status in Pennsylvania.

Due to the data gaps with respect to data quality or service area boundaries at the national level, relatively few prior studies have conducted nationwide environmental justice analyses of drinking water quality. In one national analysis, Allaire et al. (2018) employ SDWA violation records and community water system (CWS) characteristics from SDWIS to study historical trends in drinking water violations. The study uses county served data from SDWIS to match water systems to sociodemographic information obtained from the US Census. The work spans over three decades (1982-2015) and represents a national panel study on drinking water violations, but the authors do not report average water quality metrics by demographic group or relative disparities in these metrics across groups. Allaire et al. (2018) also uses the county level of analysis for identifying hotspots of water quality concern, which creates some geospatial imprecision and limits the extent of observed variation in these metrics across the US.[8] In another nationwide study, Scanlon et al. (2023) research the relationship between a modified Social Vulnerability Index (SVI) from the CDC and health-based SDWA violations, finding a positive relationship between social vulnerability and health-based violations of SDWA.

Aside from drinking water quality, which is the primary focus of this paper, environmental justice concerns and service areas also relate to water affordability. To our knowledge, two studies have evaluated the importance of service area selection in the context of water affordability. Berahzer et al. (2022) explore the implementation of different affordability metrics in a national analysis. As part of this exercise, the authors visually demonstrate the incongruence between state provided system boundaries, census designated places (CDPs), and county or tract boundaries using examples from Alabama and North Carolina. For states without available boundaries, the study uses CDPs as the relevant representation. Following Berahzer et al. (2022), El-Khattabi et al. (2023) explore variation in water bills across four US states (Arizona, Georgia, New Hampshire, and Wisconsin) using CDP boundaries. The authors also explore different boundary specifications for Arizona, the only state in the study for which statewide community water system boundaries

[8] The median county has a population of 26,551, whereas the median CWS serves a population of only 216.

exist. The authors found the results across different boundary specifications to be qualitatively similar. In related work, Patterson et al. (2023) conduct a national water affordability analysis that is primarily limited to systems that serve at least 100,000 people. The authors rely on state-provided explicit service area boundaries and modeled service areas based on municipal areas. They find that water rates in smaller systems are significantly more expensive than those in larger systems.

Overall, the academic literature on drinking water has generally focused on a subset of community water systems, often limited to a specific state or region. States with existing water system spatial boundaries (e.g., California) are over-represented in research, as are larger systems. These gaps highlight the need to conduct more nationwide analyses and to include smaller systems in environmental justice analysis, as these systems tend to have more affordability and drinking water quality concerns than the larger systems. Further, few studies have explicitly assessed the sensitivity of their results to different community water system boundary specifications. Finally, no studies have conducted national analyses of drinking water quality disparities using all recent service area boundary assignment methods or explored the differences in conclusions produced by each method.

3 Data

To compare drinking water quality and disparity measures across demographic groups, we assemble information on drinking water quality, public water system locations, and population characteristics. Data sources and cleaning procedures are described below.

3.1 Drinking Water Quality Measures

We incorporate seven measures of drinking water quality from data sources including the Safe Drinking Water Information System (SDWIS), the Six Year Review 3 and 4, the Unregulated Contaminant Monitoring Rule (UCMR) 3 and 5, and certain state-level data described in more detail below. Collectively, these indicators are intended to represent a wide range of potential drinking water quality concerns that may be studied as part of environmental justice analyses in the academic literature or for federal policy. We note that in all cases, these measures are merely proxies for potential risk, and similarly that average water system contaminant concentrations are only proxies for population exposures.

Health-based Violations of the Safe Drinking Water Act (2015-2022): SDWIS records all violations of the Safe Drinking Water Act and specifically tracks health-based violations. As the name suggests, health-based violations are instances in which a water system's activities or contaminant levels have the potential to affect public health. These violations include exceedances of the maximum contaminant levels (MCLs), exceedances of the maximum residual disinfectant levels (MRDLs), or failure to follow certain treatment technique requirements.[9] In turn, these represent failures to limit contaminant levels to below their legally enforceable threshold, failure to limit disinfectant quantities in finished water to safe levels, and failure to treat water in accordance with the SDWA. To construct this indicator, we counted all unique health-based violations in SDWIS that occurred after 2015 and prior to 2024 for a given water system. Our final sample includes $105,647$ health-based violations across $28,066$ community water systems. For systems without any health-based violations listed in SDWIS, we assume the system had no violations over this period.

Lead and Copper Rule Action Level Exceedances (1991-2021): Lead exposure has been associated with acute and chronic health effects including nervous system damage, cardiovascular disease, kidney damage, immune system disregulation, liver toxicity, reproductive harm, and various cancers (EPA, 2024d). Certain groups such as pregnant people, infants, and young children are especially vulnerable to the effects of lead exposure (ATSDR, 2020b). Lead in drinking water is regulated according to the Lead and Copper Rule (LCR) of the SDWA, which is relatively unique among National Primary Drinking Water Regulations in requiring a specific number of samples to be collected directly from consumer taps instead of at treatment plant or distribution network sampling locations. The Lead and Copper Rule also has an action level instead of a maximum contaminant level. A water system exceeds the action level for lead if the calculated 90^{th} percentile concentration exceeds 15 parts per billion (ppb) in a water system compliance monitoring period, which then requires follow-up measures to reduce lead levels across the system.[10] Given the focus on the 90^{th} percentile of sample concentrations, SDWIS reports the 90^{th} percentile lead concentration for most water system monitoring periods (EPA, 2024e). These 90^{th} percentile sample values are available for all systems serving more than 10,000 individuals, but water systems that serve fewer than 10,000 individuals and that do not have an action level exceedance (ALE) are not required to report their 90^{th} percentile concentration. Due to reporting gaps of 90^{th} percentile concentrations for systems serving fewer than 10,000 people, we instead employ the count of lead action level exceedances for each system as an indicator of lead concerns. We include all lead action level over the period from 1991 to 2021. Our final sample included 20,688 lead action level exceedances across 45,934 unique public water systems. We note a few limitations of this lead measure. First, the action level is not a health-based threshold, and as such a lead action level exceedance is

[9] In the 2023 SDWIS data vintage used in this paper, lead and copper rule action level exceedances are not considered health-based violations of SDWA unless the system fails to take appropriate steps to ameliorate the issue after a lead action level exceedance occurs.

[10] For example, an ALE would occur if more than 10% of tap water samples collected are greater than 15 ppb. In some cases, the 90^{th} percentile is calculated instead of observed if, for instance, a small water system only takes 5 samples.

only a proxy for lead concerns for any given drinking water system. Next, because lead primarily results from corrosion of lead service lines and premise plumbing, there may exist substantial variation in lead concentrations at the tap across households within a drinking water system even where an action level exceedance does not occur. See Stratton et al. (2022) for additional discussion of the limitations of lead action level exceedances in characterizing lead concerns for a particular system.

PFAS Concentrations in Drinking Water (2013-2023): PFAS are ubiquitous and long-lasting chemicals with adverse health impacts such as reproductive and developmental harm, immune system dysregulation, thyroid dysfunction, and kidney and testicular cancers (ATSDR, 2020a; Fenton et al., 2021; EPA, 2024c). We incorporate a PFAS drinking water quality metric because there is significant public interest in these chemicals, and they are also the target of a recent set of drinking water standards that are estimated to reduce their levels in drinking water for at least 80 million Americans (Andrews and Naidenko, 2020; EPA, 2024c). We create a water-system level PFAS indicator using Unregulated Contaminant Monitoring Rule (UCMR) 3 samples, provisional UCMR 5 records, and state-level sampling data.[11] The state-level data are compiled in the online dashboard PFAS Analytic Tools.[12,13] Collectively, these data include $956,552$ samples of 33 unique PFAS across $16,338$ public drinking water systems.[14] We use these samples to create an indicator for the sum of average PFAS concentrations for each unique PFAS sampled by a community water system. For example, if a system detects only PFOA and PFOS, we take the average concentration of each substance and add the two together to compute a total PFAS concentration. We assume non-detects are zero, such that a system never detecting any PFAS would receive a measure of zero. We note a few limitations of the PFAS metric in this analysis. First, a majority of water systems have no available sampling information for any PFAS, and certain systems have analyzed far fewer PFAS; these systems either do not contribute to the population-level PFAS measures or have biased low PFAS measures in comparison to systems with more sampling. Second, different sampling detection methods are used in UCMR 3 and UCMR 5, with certain PFAS Analytic Tools samples corresponding to the detection methods in UCMR 3 or 5. These differences mean that certain samples have much lower detection thresholds than other samples, even within the same system's sampling history. Next, a single detection of a particular PFAS does not

[11] UCMR 5 sampling efforts are not yet complete, so we use the latest available data as of July, 2024. For more information, see: https://www.epa.gov/dwucmr/fifth-unregulated-contaminant-monitoring-rule-data-finder

[12] See: https://awsedap.epa.gov/public/extensions/PFAS_Tools/PFAS_Tools.html

[13] We choose to incorporate state-level records because it improves the data coverage of the indicator. In addition, state sampling efforts often used more recent detection methods with lower detection thresholds, and so they were able to capture detections that may have otherwise been missed in UCMR3.

[14] The UCMR 3 and UCMR 5 records include $356,823$ samples of 29 unique PFAS across $6,246$ public water systems, gathered between 2013 and 2023. The state-level data include $651,224$ samples across 27 unique PFAS and $9,882$ public water systems. We drop PFAS analytes in the state records with fewer than $1,000$ samples overall to limit the influence of targeted sampling efforts. We also drop PFAS that are aggregations of sampling information across separate PFAS analytes. For example, we do not include combined PFOA and PFOS, which is reported in the PFAS Analytic Tools data.

necessarily represent a system's long-term levels of these substances. Finally, different PFAS have varying toxicity profiles, and so their combined concentration in a drinking water system does not directly reflect the toxicity of the system's particular PFAS mixture. In sensitivity analyses discussed in Section 5.3, we explore four alternative measures of PFAS in drinking water, show key results when limiting to samples with consistent minimum detection limits, and characterize differential sampling practices across demographic groups.

Disinfection Byproducts (2006-2019): Disinfection byproducts (DBPs) are a group of chemicals formed when disinfectants, such as chlorine, chloramine, or ozone, interact with materials in source water to create new chemicals in finished drinking water. The health effects of DBP exposure likely include bladder cancer and developmental harm (Regli et al., 2015; Padula et al., 2021). Certain unregulated DBPs are also highly toxic (Li et al., 2022). Further, elevated DBP formation may indicate that disinfectants are working less effectively, which could lead to disinfectant residual depletion and subsequent proliferation of opportunistic pathogens in the distribution system (Isaac and Sherchan, 2019). For these reasons, 11 disinfection byproducts in drinking water are regulated under the Stage 1 and Stage 2 Disinfectants and Disinfection Byproducts rules of the SDWA (EPA, 2005). The Stage 2 rule focuses on reducing concentrations of two classes of 9 DBPs. These classes are total trihalomethanes (TTHM) and haloacetic acids (HAA5), which are considered "representative of many other DBPs that may also be present in the [disinfected] water" (EPA, 2006). As part of this rule, water systems must limit total levels of four THMs and five HAA5s to locational running annual average concentrations of 80 ug/l and 60 ug/l, respectively.[15]

We construct an indicator for DBP levels in drinking water using 3 million samples of TTHM and HAA5 to generate a single DBP metric per system.[16] To do this, we take the average concentration of TTHM and HAA5 samples within each system over all samples from 2006-2019, and then we add the TTHM and HAA5 concentration averages.[17] We combine these two classes of DBPs into one measure to streamline and simplify presentation of results. Our indicator of DBP levels has several limitations. First, DBPs can vary significantly within a system's distribution system, particularly in areas with greater "water age" (i.e., the period of time water has spent in the network prior to use). Consequently, while our composite metric of DBPs is useful in characterizing DBP differences across systems, it potentially obscures differences in DBP exposure within a system that could occur if certain populations receive water with differing age profiles. Due to data limitations regarding DBP sampling locations and how these correspond to specific areas within

[15] For more information on the sampling requirements for these two groups, see EPA (2010).

[16] We source these samples two waves of the Six Year Review samples (EPA, 2016a, 2022) and samples requested from Georgia's Environmental Protection Division and downloaded from Mississippi's Drinking Water Watch website.

[17] Some systems report only the dis-aggregated chemicals that compose the four total trihalomethanes and the five haloacetic acids. For these systems, we take the average level of each constituent chemical and then sum the average levels to produce a comparable TTHM and HAA5 concentration.

distribution systems, we are not able to incorporate within-system geospatial variation in DBP exposures. Similarly, our composite measure of nine DBPs abstracts from variation in the levels of constituent DBP species, which could mask variation in risk corresponding to differential toxicity of each DBP. Related to this point, combining TTHM and HAA5 could potentially obscure differences in population exposures to each class in isolation because these DBP groups have different formation pathways and concentration distributions. As such, we describe key results when separating TTHM and HAA5 in Section 5.3 and shown in Appendix Figure 11(a) and Figure 11(b). Finally, due to changing requirements for sampling practices, we also produce disparity measures according to just pre- and post-2012 samples in Appendix Figure 12(a) and Figure 12(b) and discuss these results in Section 5.3.

Total Coliform Detections (2006-2019): For an indicator of microbial growth, we again use the Six Year Review 3 and 4 to incorporate detections of total coliform bacteria, which are monitored and regulated according to the Revised Total Coliform Rule (RTCR). Most coliform bacteria are harmless to human health, but because coliform bacteria are ubiquitous in the environment, their presence serves as a useful indicator for the presence of more harmful pathogens in drinking water such as bacteria, parasites, and viruses (EPA, 2012). Whenever coliform bacteria are detected, a water system is subsequently required to test for E. Coli, a coliform bacteria that causes illness. Because of the public health risk from any microbial growth in a water system's distribution network, total coliform is one of most common types of samples conducted as part of compliance with the SDWA. Total Coliform Rule infractions are also the most common violation of the SDWA, and so sampling for total coliform bacteria represents an important indicator of drinking water quality (Allaire et al., 2018). We make use of 18 million total coliform samples collected over the period 2006-2019 and reported with the Six Year Review 3 and Six Year Review 4. Each sample indicates whether total coliforms were detected or not, and we aggregate all of these binary samples to be one water system-level indicator for the share of samples (0-1) that are positive for total coliform bacteria over our sample period. Certain states do not report total coliform samples or tend to only store records for total coliform samples associated with potential RTCR violations, and so we exclude these states from all analysis.[18] We also drop systems with at least a 50 percent detection rate under the presumption that these systems primarily report sampling events associated with potential violations.[19] We note that sampling requirements for total coliforms were revised on April 1st, 2016, and so our measure of total coliform detections aggregates samples from periods with different regulatory requirements.[20]

[18]These states are South Carolina and Maryland, which have average system-level detection rate of 46% and 22%, respectively.

[19]This affects $1,431$ out of $157,443$ public water systems, and these are mostly non-community systems for which we lack service area boundaries.

[20]In Appendix Figure 13(a) and Figure 13(b), we demonstrate that results are very similar when limiting to alternative date ranges with more consistent sampling requirements.

Arsenic Concentrations (2006-2019): Arsenic exposure in drinking water has been associated with myriad adverse health effects including diabetes, cardiovascular disease, developmental impacts, and skin, bladder, and lung cancer (EPA, 2023d). Arsenic is our only primarily geogenic (i.e., naturally occurring) drinking water contaminant, and as such it displays significant clustering in semi-arid regions such as the Western and Southwestern US (Scanlon et al., 2023). We use the Six Year Review 3 and 4 to determine arsenic concentrations in drinking water.[21] In total, we make use of 598,662 samples of arsenic in drinking water and compute the system-level average from 2006-2019. We drop any samples with concentrations above 150 mg/l to limit the influence of outlier concentrations and to remove potentially mis-labeled units of measurement.[22]

Nitrate Concentrations (2006-2019): We use the Six Year Review 3 and 4 to determine nitrate concentrations in drinking water, and we supplement this with samples from Georgia and Mississippi's Drinking Water Watch websites to ensure national coverage of the metric. Nitrates are primarily an agricultural pollutant, and so they tend to be higher in areas with greater levels of fertilizer application on farms or more animal agricultural runoff. [23] Nitrate exposure in drinking water is associated with an acute adverse health impact on newborns known as methemoglobinemia or "blue baby syndrome," although it has also been associated with colorectal cancer, thyroid disease, and neural tube defects (Ward et al., 2018). Nitrate levels are also an outsized portion of all SDWA violations (Allaire et al., 2018). Some states and certain systems do not always report nitrate concentrations in their compliance monitoring data, instead reporting Nitrate and Nitrite concentrations when the combined level of both is below the regulatory threshold for either.[24] This compliance reporting practice is explicitly permitted by EPA compliance reporting authorities (EPA, 2020b). Since nitrate-nitrite combined samples are usually low concentrations that are in compliance with regulatory thresholds and nitrite converts to nitrate with increasing water age in the distribution network,[25] we use nitrate-nitrite samples where available as a reasonable proxy for nitrate levels overall to help fill in national coverage of this metric (EPA, 2002a). We drop any samples with concentrations above 500 mg/l to limit the influence of outliers and because these samples may have incorrect concentration units of measurement. Collectively, we make use of 3,123,444 samples of Nitrate or Nitrite-Nitrate in drinking water.

[21] As before, we supplement this with samples requested from Georgia's Environmental Protection Division and downloaded from Mississippi's Drinking Water Watch website to ensure national coverage of the metric.

[22] The legally enforceable limit of Arsenic in drinking water is 0.01 mg/l.

[23] Water systems that use chloramine to disinfect water may also see heightened nitrate levels due to the decay of chloramine into ammonia and in turn nitrite and nitrate through biological nitrification in the distribution system (Liu et al., 2020; NHDES, 2021). However, such nitrification of the distribution system would affect tap-levels of nitrates without being observable at treatment plants or entry points where our sampling data is collected.

[24] These states are Delaware, Louisiana, Minnesota, Missouri, Montana, Nebraska, North Dakota, Virginia.

[25] The maximum contaminant level for nitrite is 1 mg/l, and the maximum contaminant level is 10 mg/l for nitrate.

3.2 Service Area Boundaries

We use five service area boundary representations to compare drinking water quality measures across demographic groups and with other indicators of environmental quality.

County Boundaries: EPA requests county served information from water systems as part of the Safe Drinking Water Information System (SDWIS), and the consistent reporting of primary county served is a rationale for frequent use of this geography for determining demographics at the water system level (EPA, 2019). However, county served information is not always provided in SDWIS.[26] Moreover, there are occasional issues with the location specified as a service area in these fields. To limit possible incongruities between service area representations, we assign county identifiers based on a spatial intersection of county polygons with the Hydroshare (2022) geographic location. Service areas overlapping multiple counties are assigned the county with the greatest overlapping surface area.

Zip code Boundaries: We source zip code served information from SDWIS and the Unregulated Contaminant Monitoring Rule 3, 4, and 5, where all zip codes served across each dataset are dissolved into a single polygon shape for a given water system.[27] For example, if a water system is listed as serving different zip codes in SDWIS and in one of the UCMR datasets, we include both zip codes as being served by the water system and combine each zip code shape into a unified geospatial polygon. Zip codes served are available for 16,470 public water systems, and hence this boundary layer has a more limited number of systems than are available in other layers.

USGS Boundaries (2022): The US Geological Survey produced geospatial data of 18,806 water system service areas (Buchwald et al., 2022). The purpose of the USGS data layer differs from the other boundary representations employed in this paper, and as a result the water system spatial boundaries also differ from the other geospatial data. In particular, USGS efforts were primarily aimed at developing a national public water supply use model that could be used to estimate anticipated withdrawal needs and flow of surface waters across the coterminous U.S. As such, water system areas often include the entire supply region that may purchase or otherwise use water from a given system's intake infrastructure. The USGS water system service area layer also differs from the other data in making use of the National Wall-to-wall Anthropogenic Land Use Trends (NWALT) information and the National Land Use Dataset (NLUD) in estimating the likely extents of public water supply regions (Falcone, 2015; Theobald, 2014). Much like the zip code boundary

[26] In some cases, city or zip code information is provided instead. For more information, see: https://www.epa.gov/ground-water-and-drinking-water/safe-drinking-water-information-system-sdwis-federal-reporting

[27] Access SDWIS data at https://echo.epa.gov/tools/data-downloads/sdwa-download-summary and UCMR records at https://www.epa.gov/dwucmr/occurrence-data-unregulated-contaminant-monitoring-rule

layer, the USGS information has fewer system representations than the county, EPIC, or EPA service area boundary data.

EPIC/Simple Lab Boundaries (2022): The Environmental Policy Innovation Center (EPIC) and Simple Lab, in consultation with the Internet of Water coalition, created a provisional nationwide dataset of water system boundaries in 2022. This dataset classifies boundaries into three tiers based on data quality. Tier 1 boundaries are digitized boundaries that were previously created by state efforts.[28] Tier 2 boundaries use municipal boundaries as proxies for water system boundaries. Tier 3 boundaries are estimated circular boundaries around an approximated location for the water system.[29] Approximated locations for tier 3 water systems can be based on county polygon centroids, zip code centroids, facility locations if available in SDWIS, or water system address. Tier 1 service area polygons are available for half the population served by public water systems (roughly 156 million individuals), and Tier 2 city-boundary polygons have been matched to a public water system (PWS) for a further 35% of the population served (111 million individuals).[30]

EPA Office of Research and Development Boundaries (2024): The most recent water system service boundary data is described in EPA (2024b). It uses a decision tree framework to identify all U.S. census blocks likely to be served by public water and then an array of subsequent matching methods to assign water system identifiers to these likely service areas. The decision tree approach is validated using 3 states with high-quality and publicly-available boundaries. These states are California, Connecticut, and New Jersey. For each state, the decision tree identifies the share of 700,000 census blocks that are served by public water or private wells. The model uses eight information inputs including amount of impervious surfaces, 2020 housing unit density, 1990 housing unit density, the percent housing unit change from 1990 to 2020, 1990 housing unit public water connection, 1990 public sewer connection, area, and distance to public intake. For every geography, these information fields were classified into 20 unique geographic types; these types are then characterized as either on public water or not on public water. Next, EPA (2024b) use water system name and facility location matching procedures including a random forest machine learning model to assign likely service area regions to specific water system IDs based on available information. The EPA (2024b) boundaries also include publicly-available state boundaries where available, and these correspond to the Tier 1 boundaries in the EPIC service area boundary dataset. As such, the EPA (2024b) boundaries are identical to the EPIC service area boundaries for slightly less than half of community water systems

[28] For a recent summary of the quality of this Tier 1 data, see EPA (2024a).

[29] Tier 3 systems represent lower-quality boundary approximations, which is why some research excludes them entirely from analysis (e.g., Scanlon et al. (2023)).

[30] See Hydroshare (2022) to download consolidated service area polygons and for more information on the modelling approach.

representing just over 150 million individuals served by public water.

3.3 Population Characteristics

We use the American Community Survey (ACS) 5-year data for 2017-2021 to determine demographics of public water systems (U.S. Census Bureau, 2023). We use the 2021 ACS 5-year estimates because they provide data for all areas and are more reliable than 1-year or 3-year estimates, especially for rural areas with lower populations (U.S. Census Bureau, 2024). We also incorporate indicators of community environmental pollution burden from EJSCREEN, the US EPA Environmental Justice Mapping and Screening Tool (EPA, 2023b).[31] EJSCREEN also uses the ACS to construct its sociodemographic variables (USEPA, 2022), and so the choice to use ACS 5-year records associated with 2021 ensures correspondence between Census division polygons, population information, and EJSCREEN variables. We generate variables for socioeconomic characteristics and EJSCREEN environmental indicators for each water system across all service area boundary representations using the areal apportionment methods of EJSCREENBatch, a R-based package developed by researchers in EPA's Office of Water to simplify national environmental justice analyses (El-Khattabi et al., 2023). In this areal apportionment procedure, we compute the population characteristics of a specified boundary of interest (i.e., water system boundary) by weighting the population characteristics of all intersecting census block groups according to the fraction of the population contained within the portion of the block groups that overlap with the specified boundary. To refine population estimates at the sub-block group level, we use a 30x30 grid raster file of decennial Census information created by NASA's Socioeconomic Data and Applications Center (SEDAC, 2017).

4 Empirical Methods

The following sections detail how we construct measures of drinking water quality and disparity measures. We then describe our approach to mapping drinking water quality and areas of potential environmental justice concern. Finally, we describe a set of correlational regression models that characterize associations between measures of drinking water quality and socioeconomic vulnerability.

Drinking Water Quality by Demographic Group: We construct average demographic-specific drinking water indicators by population-weighting the following equation. Let i index one of the seven measures of drinking water quality, j represent a population demographic group, and k represent a public water system.

[31] For the full documentation of EJSCREEN, its data, and the environmental and sociodemographic factors it employs, see USEPA (2022).

$$Indicator_{ij} = \frac{\sum_{k \in PWS}^{K} PopulationShare_{ijk} * PopServed_{ik} * Indicator_{ijk}}{TotalPopulationServed_j} \tag{1}$$

The construction of Equation 1 is analogous to constructing a population-weighted average for any given drinking water indicator i and demographic group j, however the average is informed by the share of a demographic group served by a particular water system according to the specific service boundary type that is employed. We use boundary-invariant total population served information, $PopServed_{ik}$, to ensure that differences in population-weighted drinking water quality are driven by different estimates of demographic composition for each system rather than varying population size. The drinking water indicators are listed and described in Section 3. We select eight demographic groups that allow for two types of general comparison. The first pair of demographic categories compare average drinking water quality measures for non-Hispanic White populations to those of American Indian, Asian, Black, Hispanic, or Pacific Islander populations. The second pair of disparity measures compare individuals with incomes below twice the federal poverty limit to individuals with incomes above twice the poverty limit.

Disparity Measures: To simplify comparison of disparities in drinking water quality across service area boundary types, we construct disparity measures that convey the relative prevalence of a drinking water quality concern for a group u with potentially heightened socioeconomic vulnerability in comparison to a mutually exclusive group v. Specifically, let these demographic groups be:

$$u \in \{American\,Indian,\ Asian,\ Black,\ Hispanic,\ Pacific\,Islander,\ Below\ 2X\ Federal\ Poverty\ Limit\},$$

$$v \in \{Non - Hispanic\,White,\ Above\ 2X\ Federal\ PovertyLimit\}$$

In words, we generate disparity metrics for people of color and for individuals with incomes below twice the federal poverty limit.[32] People of color are compared to the percent non-Hispanic White population, whereas low-income populations are compared to the population with incomes above 2x the federal poverty limit. For each group with potentially heightened socioeconomic vulnerability, u, we express disparity measures for each drinking water quality indicator i as:

$$Disparity\ Measure_i = \frac{Indicator_{iu}}{Indicator_{iv}} \tag{2}$$

Depending on the drinking water quality indicator, these disparity measures are concentration ratios

[32] Throughout this paper, we use the terms people of color and minority populations interchangeably.

(e.g., ug/L of arsenic) or prevalence ratios (e.g., frequency of health-based violations). A prevalence or concentration ratio of 1 indicates equal prevalence of the drinking water concern across the population groups, a value of less than one indicates less prevalence of the drinking water concern for the demographic group of potential environmental justice concern, and a value greater than one indicates higher potential risk for the demographic group of interest. For certain analyses such as sensitivity tests and bivariate maps, we combine each minority population group into an aggregate category to simplify the presentation of results.

Mapping Drinking Water Indicators: We map drinking water metrics at the national level using the EPA ORD service area boundaries, and we also present national and sub-national bivariate maps that plot drinking water quality in combination with measures of socioeconomic vulnerability.

To create maps at the census division level, we start by spatially intersecting all service areas with census block groups.[33] This produces a census block group dataframe, where each public water system is associated with all intersecting census block groups (i.e., PWS-by-CBG). We next join drinking water indicators to the public water system such that all PWS-by-CBG rows in the dataframe are associated with a drinking water quality indicator. For census block groups intersecting multiple drinking water system service area polygons, we average indicators across all water systems to retain a single average value for each CBG per indicator. As such, our maps portray spatially-aggregated water quality measures, rather than water system-level drinking water quality.[34] We then construct national maps for each water quality indicator. To ease visualization of the indicator distribution in the presence of significant right skew, the maps use the 3rd quartile value as a maximum cutoff point for the map color scale.[35] Census areas with indicator values that are greater than this cutoff are marked as greater than that value, and each area with a lower indicator value keeps its original value. This ensures a more even distribution of areas across the color gradient.

We also produce bivariate maps that demonstrate the relationships between drinking water quality and factors that are associated with greater social vulnerability. While bivariate maps do not convey causal relationships, they are useful for locating hotspots of environmental justice concern and for demonstrating variation in such concerns within and across states.[36] We also generate sub-national maps to highlight the heterogeneity in both drinking water concerns and population demographics at the census block group to

[33]We choose to convert service area boundaries to census divisions because service areas alone are often hard to see at a national scale due to overlapping and irregular boundaries of relatively small shapes.

[34]We generate the simple mean drinking water indicator across intersecting public water systems without weighting by population across public water systems. We choose not to weight by population because we do not observe the share of a CBG's population that is served by each intersecting water system.

[35]For health-based violations, we select a maximum cutoff point that is higher than the third quartile since many systems have no violations.

[36]For the drinking water indicators in the bivariate maps, we do not use traditional quartile breaks due to the presence of many zero or null observations across census block groups. Rather, we define indicator-specific break points in the drinking water measures to partition the distribution into three intuitive dimensions ("low", "medium", and "high"). The demographic variables representing race and income are broken up into terciles for the bivariate maps.

motivate a higher level of geospatial precision when conducting environmental justice analyses.

Regression Analysis: We test for associations between community characteristics and drinking water quality. We consider dimensions of community heterogeneity related to socioeconomic vulnerability as well as cumulative pollution burden, drawing from the environmental indicators provided by EJSCREEN. We note that this analysis is associational and descriptive in nature. Let i represent a water system and d represent one of the drinking water indicators described in Section 3. Consider the following regression equations:

$$y_{id} = \beta' X_i + \nu_{id} \tag{3}$$

$$y_{id} = \gamma' E_i + \nu_{id} \tag{4}$$

In Equation 3 and Equation 4, y_{id} represents the drinking water indicator d for a specific water system i. These values are regressed on the vectors X_i and E_i, which include demographic characteristics and environmental hazard variables respectively. Our first set of regressions calculates the relationship between drinking water quality measures and characteristics of a water system's population served including the percent American Indian, Asian, Black, Hispanic, Pacific Islander, and percent twice below the federal poverty level. We also include variables for water system size classifications, water source, and whether the system is a Tribal utility.[37] The environmental variables included in E_i relate to lead paint, Ozone, PM 2.5, proximity to a toxic release facility, wastewater discharge, and proximity to an EPA designated Superfund site.[38] In these ordinary least squares regressions, the coefficients of interest are β and γ, which represent the change in the outcome variable according to a one unit increase in the independent variable. In all cases, we refer to associations with p-value of less than 0.1 as statistically significant.

5 Results

In the following sections, we first provide a detailed description of average levels each drinking water quality measure across all drinking water systems. We then summarize these measures across demographic groups and geographic regions, and we characterize disparities using intuitive disparity measures, bivariate maps,

[37] We include both Tribal system status and the percent American Indian to account for the drinking water quality experienced by American Indian individuals, irrespective of Tribal system status.

[38] We drop indicators for air toxics cancer risk and air toxics respiratory hazard index, as these are constructed from the other air pollution information provided and would therefore be highly correlated with these variables.

and regression-based statistical tests. We provide supplemental analysis explaining why different geospatial methods can lead to different conclusions. We conclude with sensitivity tests and a discussion of limitations.

5.1 Drinking Water Quality and Disparity Measures

We provide novel evidence on the extent of disparities in drinking water quality in this section. As detailed below, we find potential environmental justice disparities with respect to all drinking water quality metrics investigated in this analysis.

Health-based Violations of the Safe Drinking Water Act (2015-2023): We summarize the average number of health-based violations across public water systems and according to each boundary representation in Table 1. The average total number of health-based violations per system is 1.3 to 1.4 from 2015-2023 according to the most complete boundary data, with 77% of systems having zero health-based violations in this period.[39] According to the subset of systems with USGS boundaries, the average number of violations is 1.6; the subset of systems with zip code information have a lower average number of violations at 0.8. These differences in violation averages for USGS or zip code boundaries relate to a smaller set of observed systems. There is right skew in the count of health-based violations; Appendix Table A4 shows that the average number of health-based violations among systems with at least one violation is roughly 5.8.

Next, we summarize the average population-weighted count of health-based violations in systems serving each demographic group in Table 2. We illustrate disparities in the count of health-based violations across groups in Figure 1(b), which characterizes the magnitude of disparities using the convention of prevalence ratios described in Section 4. We find that American Indian, Black, and Hispanic populations all experience more health-based violations than non-Hispanic White individuals according to most boundary representations, with American Indian populations notably experiencing 2 - 3 total health-based violations in comparison to 0.8 for non-Hispanic White populations.[40] Low-income individuals also experience more health-based violations than non-low-income populations across all boundary types. When observing the prevalence ratios for each demographic group in Figure 1(b), two findings emerge. First, potential risk often increases when moving from the least geospatially precise boundaries to more accurate boundaries, although this conclusion may also relate to data completeness for USGS and zip code boundaries. For example, between county and EPA boundaries, American Indian populations experience between 2.56 to 3.29 times more health-based violations than those serving primarily non-Hispanic White populations, a 29% gap between the lowest and highest estimate of disparity. This finding suggests that the magnitude of

[39]The county, EPIC, and EPA ORD datasets are the most complete in terms of system coverage, each with at least 44, 000 systems represented.

[40]For numeric characterization of the prevalence ratios, see Table 3.

an environmental justice concern may be under-estimated when using incomplete or imprecise boundaries. Moreover, conclusions regarding the presence of a disparity for Hispanic populations depend on the service area boundary representation selected, where county boundaries suggest fewer health-based violations while all other boundaries suggest more frequent violations among systems serving Hispanic populations.

We also characterize geospatial heterogeneity in the number of health-based violations and potential for environmental justice concerns. Figure 1(a) maps violation counts nationwide, demonstrating that health-based violations occur throughout the US, although certain states have more non-compliance concerns than others. In particular, systems in Texas, Oklahoma, Louisiana, Kentucky, and Alaska all have numerous CBGs with an average of at least 10 health-based violations from 2015-2023. To determine how these clusters of violations correspond to potential environmental justice concerns, we also present bivariate maps that show the number of health-based violations alongside the percent people of color in Figure 8(a) and the percent of individuals living below twice the federal poverty line in Figure 8(b).[41] We note some areas along the southwest border states that have a high percentage of people of color and a high count of health-based violations. Additionally, we see higher violation counts and higher percent people below twice the federal poverty level in the South, specifically in the northeastern part of Texas and in Oklahoma. In addition, Alaska has high rates of health based violations, people of color, and people living below twice the federal poverty level, reflecting a potential environmental justice hotspot with respect to health-based violations.

We conclude with regression-based statistical characterization of disparities in the number of health-based violations across demographic groups while controlling for water system characteristics in Table 4.[42] The first column of Table 4 displays coefficients related to demographic groups when controlling for water system size, water source type, and whether the system is operated by a recognized Tribe. Systems serving a greater share of American Indian, Hispanic, and low-income individuals tend to have statistically significantly more health-based SDWA violations, confirming that some of the disparities observed in Figure 1(b) persist even when controlling for system characteristics and share of the system that is low-income. For example, the coefficient with respect to American Indian of 5.4 in column (1) suggests that a ten percentage point increase in the share of a service population that is American Indian is associated with roughly 0.5 more health-based violations. This increase is over a third of the system-wide mean count of health-based violations at 1.3. The share of a service population that is Black is associated with a small but statistically significant decrease in the health-based violation count. This finding contrasts with the raw difference in mean violation counts for this group, suggesting that part of the disparity in violation counts may be statistically explained by

[41] In Appendix Figure 1(a) and Figure 1(b), we also include simple demographic maps to help provide a baseline for comparison in the bivariate maps, highlighting racial and economic demographics across the United States.

[42] These regressions are based on EPA ORD service area boundaries, but we also show regressions with respect to the EPIC boundaries in Table A5.

differences in typical water system size or source water. Meanwhile, a ten percentage point increase in the share of a service population that is Hispanic is associated with a 0.26 additional health-based violations conditional on other water system characteristics. A similar 10 percentage point increase in the share of a service population with incomes below twice the federal poverty limit is associated with 0.2 additional health-based violations. Asian and Pacific Islander populations tend to be served by water systems with fewer health-based violations, which can also be observed in the prevalence ratio bar plots. As for system size categories, very small and small systems are more likely to experience health-based violations than medium-sized systems, which are the omitted category of system size. Conversely, large and very large water systems tend to have fewer health-based violations than smaller systems. Groundwater-sourcing systems also tend to have fewer violations.

Lead Action Level Exceedances (1991-2021): We summarize our measure of lead in drinking water, the count of lead action level exceedances (ALEs), according to each boundary in Table 1. The average count is similar at roughly 0.45 per system irrespective of the boundary representation employed, with 78% of all systems never experiencing a lead ALE from 1991 to 2021. As with the health-based violations, we observe that there is right skew to the distribution of lead ALEs across systems, where the average number of ALEs for systems with at least one violation is over 2 according to all boundary types as shown in Appendix Table A4.

We summarize the average population-weighted count of ALEs among systems serving each demographic group in Table 2, and we illustrate disparities across these groups in Figure 2(b). We find that Asian and Black populations are served by water systems with more lead ALEs irrespective of the boundary representation employed. Asian populations have the greatest frequency of lead ALEs of any group with 1.7 to 2 ALEs, at least 1.5 times as many ALEs as non-Hispanic White populations according to all boundary types. The magnitude of this disparity measure ranges from 1.48 to 2.1 depending on the service area boundary employed, or a 42% gap between the lowest and highest estimated prevalence ratio. Black populations also tend to be served by water systems with more lead ALEs irrespective of the boundary type, at 1.1 to 1.4 ALEs and prevalence ratios ranging from 1.1 to 1.3 depending on the service area boundary representation. Conversely, conclusions regarding the presence of a disparity in lead ALEs for Hispanic and low-income individuals depend on the service boundary representation employed. For example, zipcode and USGS boundaries suggest no presence of a disparity, while the other boundary types suggest that Hispanic populations are served by water systems with more ALEs. In contrast to the findings for health-based violations, we do not always observe a pattern of greater disparities with increasing boundary precision; county boundaries suggest the greatest disparity for Asian populations. However, less-complete USGS and zip code boundaries suggest disparities of lower magnitude for Asian and Black populations.

We map the count of ALEs in Figure 2(a). The map shows that water systems with more lead ALEs are concentrated in the northeastern US and the Midwest. These findings could be attributed to older infrastructure in these regions, which is described in the Drinking Water Infrastructure Needs Survey (EPA, 2023a). Ohio has notably high levels of lead ALEs in comparison to other states, which we explore further in Section 5.2.4. We also observe pockets of more frequent ALEs in Alaska, parts of California, and the coastal Pacific Northwest. To explore the potential for environmental justice hotspots,[43] we present bivariate plots of the number of lead ALEs alongside the percent people of color in Figure 9(a) and the percent of individuals living below twice the federal poverty line in Figure 9(b). We observe that many areas with the greatest share of people of color and the highest number of lead ALEs are observed frequently in California, Alaska, and in some large cities such as Chicago. Clusters of more frequent lead ALEs and low-income populations can also be observed in Alaska, California, Missouri, and parts of the Northeast.

Finally, we conduct a statistical test of disparities in the number of lead ALEs across demographic groups conditional on other water system characteristics. These results are displayed in column (2) of Table 4. Water systems that serve a greater share of Asian individuals tend to have statistically significantly higher counts of lead ALEs, whereas systems serving a greater share of Hispanic and low-income individuals tend to have fewer lead ALEs. A ten percentage point increase in the Asian share of a service population is associated with 0.08 more lead ALEs, a 17% increase from the mean of 0.45 ALEs per system. American Indian, Black, and Pacific Islander populations do not have statistically significantly different counts of lead ALEs conditional on other controls. Regarding the other system characteristics, large and very large systems have more lead ALEs than the omitted category of medium-sized systems, while small and very small systems have fewer lead action level exceedances.

PFAS Concentrations (2013-2023): We summarize the sum of PFAS concentrations across water systems with sampling data in Table 1. These total concentrations represent the sum of average concentrations across 33 unique species of PFAS in parts per trillion (ppt).[44] The average total concentration of PFAS is 5 - 6 ppt, with 65 to 70% of systems sampling for PFAS never detecting the chemicals. We note that these figures are not necessarily representative of all systems nationwide, as less than one fourth of community water systems have any PFAS sampling history. For example, average concentrations are 5 ppt for the more complete county, EPIC, and EPA boundaries but slightly higher at 6 ppt according to the subset of systems for which we have zip code served data. Nevertheless, this measure of PFAS in drinking water represents the

[43] As previously described, potential hotspots at the neighborhood and even household level will not be captured by system-level lead ALE counts.

[44] We assign concentration values of zero to all non-detection samples.

sampling history of water systems serving 270 million people. While most systems in our data never have a PFAS detection, systems that have detected PFAS tend to have average total concentrations of 17 to 19 ppt as shown in Appendix Table A4.

We summarize the average concentration of all PFAS across demographic groups in Table 2, and we also illustrate disparities across these groups in Figure 3(b). Asian, Black, and Hispanic communities are served by water systems with higher average PFAS concentrations than non-Hispanic White populations irrespective of the service area representation employed. Of all groups, Hispanic communities are served by water systems with the highest PFAS levels at 13 to 17 ppt on average. However, conclusions regarding the presence or absence of an environmental justice concern depend on the boundary representation employed with respect to American Indian and low-income populations. In the case of American Indian communities, the county, zip code, and USGS boundaries all point to a lack of disparity in PFAS levels, while the more complete and spatially-refined EPIC and EPA boundaries suggest elevated concentrations among water systems serving this population.

We map PFAS concentrations in Figure 3(a). This map highlights that certain areas are much more likely to have sampled for PFAS in drinking water, whereas large stretches of the country have limited data availability. States with more PFAS sampling include California, Massachusetts, New Jersey, North Carolina, Colorado, and Illinois. Among states that have sampled across most of their drinking water systems, Alabama, New Jersey, and North Carolina appear to have the relatively frequent PFAS detections at elevated concentrations. To shed further light on the disparities for particular groups observed in Figure 3(b), we present bivariate maps of PFAS and the % people of color in Figure 10(a) and % low income in Figure 10(a). These maps show notable environmental justice hotspots with respect to PFAS in New Jersey, North Carolina, and California. We perform supplemental analysis of PFAS levels in New Jersey in Section 5.2.4

We display regression-based tests of statistical significance in the extent of disparities in PFAS detections across demographic groups in column (3) of Table 4. We find that Asian, Black, and Hispanic populations are served by water systems with elevated PFAS, and this difference is statistically significant after controlling for other water system characteristics and share of the population that is low-income. In particular, a ten percentage point increase in the share of a service population that is Asian is associated with an additional 1.6 ppt of PFAS. A similar shift in the share of the service population that is Black or Hispanic is associated with a 0.6 and 0.8 ppt increase in total PFAS concentrations. We do not observe statistically significantly elevated PFAS detected for American Indian populations or tribal utilities in this model despite noting the presence of a disparity according to EPA ORD boundaries in Figure 3(b). These findings imply that the the elevated PFAS concentrations for systems serving American Indian individuals are either not large enough to be statistically distinguishable from zero or that they may be statistically explained by other factors such as water system characteristics. Next, we note some interesting patterns across water system size categories. The very largest systems are significantly likely to have 2 ppt higher PFAS concentrations, and small systems have roughly 2 ppt lower PFAS concentrations. These discrepancies across small and large systems could be due to differences in sampling data availability. We note that certain point estimates may be unexpectedly large in magnitude because they represent inference from relatively small underlying populations or minimal shifts in the related independent variables. For example, a ten percentage point increase in the share of a service population that is Pacific Islander is associated with 8 ppt lower PFAS concentrations.

Disinfection Byproducts (2006-2019): Our measure of disinfection byproducts in drinking water is the sum of the average concentrations of trihalomethanes and haloacetic acids among samples collected from 2006 to 2019. We summarize this metric in Table 1, showing that the average system has a concentration of 29-30 $\mu g/l$ according to county, USGS, EPIC, and EPA ORD boundaries. Due to lower sample size and lack of representativeness, use of zip code boundaries suggests higher average concentrations at 41 $\mu g/l$. The higher concentrations observed when limiting to systems with zip code served information is likely because all large systems have available zip code served data, and smaller systems are less likely to have available zip code served information. This different subset of systems biases estimates upwards because large systems tend to have differences in sourcewater characteristics and distribution network size that contribute to higher DBP levels. Across all boundary representations, the share of systems with DBP concentrations of zero is 17 to 19% except for zip code boundaries, which have a lower share (7%) of systems with concentrations of zero due to the differential representation of larger systems.

We summarize the average DBP concentrations experienced by different demographic groups in Table 2, and we also illustrate disparities across these groups in Figure 4(b). Black and low-income populations have elevated DBP levels in drinking water irrespective of the boundary representation selected, while conclusions regarding the presence of a disparity for Asian populations depend on the service area boundary selected. We note that the disinfection byproduct disparity metrics tend to be more clustered around one, which is partly because the distribution of DBP concentrations across systems exhibits less skew. We map combined disinfection byproducts concentrations in Figure 4(a), which also highlights the regions that have very high DBP levels and others that either have low DBP levels. For example, large regions of states including Arkansas, Kentucky, Missouri, Iowa, and Nebraska have average combined levels of TTHM and HAA5 that are over 100 $\mu g/l$.[45] We observe relatively low regulated DBP levels in some arid Western states such as California, Nevada, and Arizona, which could relate to differential DBP precursors in source waters in these

[45] The occurrence concentrations reported in this map are not reflective of potential compliance assessment with MCLs, which for DBPs is based on locational running annual average concentrations.

states. We illustrate DBP levels in combination with % people of color in Figure 11(a) and % low income in Figure 11(b). These maps suggest that systems with a high share of low-income individuals in the Midwest in states such as Oklahoma and Northern Missouri also often have high concentrations of DBP levels.

Tests for statistical significance of disparities in levels of DBPs across demographic groups are displayed in column (4) of Table 4. These regressions suggest that low-income individuals are statistically significantly more likely to be served by water systems with elevated concentrations of DBPs. The coefficient suggests that a ten percentage point increase in the share of a service population that is low income is associated with 2.1 $\mu g/l$ more DBPs conditional on water system size and sourcewater characteristics. We do not observe any statistically significant and elevated associations between DBP concentrations and race or ethnicity, although we note systems serving a greater share of Asian and Hispanic populations as well as tribal utilities tend to have statistically significantly lower DBP levels. These findings could relate to relatively lower DBP levels in Western states as mentioned above. Finally, very small systems and groundwater sourcing systems tend to have statistically significantly lower DBPs.

Total Coliform Detection Rate (2006-2019): At the national level, drinking water systems have an average detection rate for total coliform bacteria of roughly 2% according to all service area boundary types. As shown in Table 1, roughly 30% of systems never have a single detection of total coliform bacteria when using the more-complete county, EPIC, and EPA ORD boundary data, however this figure is lower at 21% when computing it over the set of systems with zip code served information. Among systems that ever have at least one detection, the average detection rate is closer to 2.7% as shown in Appendix Table A4.

We summarize the average total coliform detection share experienced by each demographic group in Table 2, and we illustrate disparities across these groups in Figure 5(b). Asian, Black, Hispanic, and Pacific Islander populations are served by drinking water systems with elevated total coliform detection shares in comparison to the non-Hispanic White population irrespective of the service area boundary type. For low-income populations, conclusions regarding the presence of a disparity depend on the type of boundary representation selected, with county boundaries suggesting no elevated total coliform detections while all other boundaries suggesting potentially elevated detection likelihood for low-income populations. We map combined total coliform detection shares in Figure 5(a), and we thus show which states have had a higher share of positive samples throughout our study period. Contrary to some of the other drinking water quality measures, there are notable data gaps for certain states in the Six Year Review 3 and 4 records including California, Massachusetts, and Michigan, and we additionally drop South Carolina and Maryland due to different reporting practices in these states. We observe geographic concentrations of elevated total coliform detection shares in Arizona, Louisiana, Nebraska, Tennessee, Georgia, and parts of the Western United

States such as Idaho. We illustrate total coliform detection shares levels in combination with % people of color in Figure 12(a) and % low income in Figure 12(b). These maps suggest potential hotspots for total coliform detections and people of color in Alabama, Alaska, Arizona, and parts of Texas, whereas clusters of low-income individuals and drinking water systems with elevated total coliform detection shares can be observed along the Mississippi River, Arizona, Nebraska, and southern Alabama.

We test for statistical significance in disparities in total coliform detection shares across demographic groups and present these results in column (5) of Table 4. Total coliform detection shares are positively and statistically significantly associated with the share of a service population that is American Indian, Pacific Islander, and low-income. The results suggest that a 10 percentage point increase in the share of a service population that is Pacific Islander is associated with a 0.12 percentage point increase in the total coliform detection rate.[46] Detection shares are negatively and statistically significantly associated with the Hispanic share of a service population. The remaining demographic groups are not statistically associated with total coliform detection shares. Of all the drinking water indicators, total coliform regression results differ the most from the raw population differences presented in Figure 5(b) and Table 2, where we show that Asian and Black populations are served by systems with higher unconditional detection shares. This discrepancy could be due to the fact that disparities for these groups are statistically explained by differences in typical water system size or source water characteristics. In particular, the very largest water systems tend to have much higher total coliform detection shares in comparison to all other water system size categories, with these systems seeing a 4.4 percentage point greater detection rate than the omitted system size category. In addition, systems that source from groundwater have marginally greater total coliform detection shares, which could reflect that groundwater systems typically use less disinfectant for their sourcewater. Lower disinfectant use increases the likelihood of microbial growth in the distribution system.

Arsenic Concentrations (2006-2019): The average concentration of arsenic in community water systems from 2006-2019 is 0.6 - 0.7 $\mu g/l$ or *ppb*, with slightly over 70% of systems never detecting arsenic as shown in Table 1. Among the roughly 28% of systems that ever have at least one detection of arsenic, the average concentration is 2.3 $\mu g/l$ for all boundary types except for zip codes (see Appendix Table A4). For context on these average levels of arsenic, the legally enforceable maximum contaminant level for arsenic of 10 $\mu g/l$. The estimated average concentration is fairly consistent across service area types and only differs when limiting the sample to systems with available zip codes, where the average level is 0.5 ug/l due to lower system count for those records. We summarize the population-weighted average arsenic concentrations among systems serving each demographic group in Table 2, and we illustrate disparities across these

[46] For example, this point estimate could represent a shift from the mean of 2 percent to 2.12 percent.

groups in Figure 6(b). American Indian, Hispanic, Pacific Islander, and low-income populations are served by systems with elevated arsenic concentrations in comparison to either the non-Hispanic White population or the non-low income population. We observe the highest concentrations among American Indian and Hispanic populations, who on average are served by systems with concentrations of 0.7-1.0 and 0.7-0.8 ug/l, respectively. For American Indian populations, potential arsenic disparity measures range from 1.67 to 2.43 between the county and EPA boundaries, suggesting that the magnitude of this disparity could be underestimated by as much as 45% depending on the service area boundary employed. For Asian populations, conclusions regarding the presence of a disparity depend on the service area boundary type employed, with all boundary types except the USGS data suggesting higher arsenic levels for this group.

We map arsenic concentrations in Figure 6(a), illustrating that arsenic tends to be detected at higher concentrations in the Western United States. Clusters of elevated arsenic levels can be observed in California, Texas, Nebraska, Nevada, and pockets of the Northwestern US. Arsenic is seldom detected in the Eastern and Southeastern US. We illustrate arsenic concentrations in combination with % people of color in Figure 13(a) and % low income in Figure 13(b). These maps suggest potential hotspots for arsenic exposures to people of color in parts of California and Southern Texas, whereas clusters of low-income individuals and elevated arsenic levels can be observed in the same regions as well as Alaska and Nebraska.

We show statistical tests of association between population characteristics and arsenic levels in column (6) of Table 4. Arsenic levels are positively and statistically significantly associated with the share of a service population that is American Indian, Asian, and Hispanic. The coefficient for % Hispanic suggests that a 10 percentage point increase in the Hispanic share of a water system's service population is associated with 0.17 ug/l higher concentration of arsenic, a 25% shift from the mean concentration across all systems. Meanwhile, a 10 percentage point increase in the share of a service population that is American Indian is associated with 0.09 ug/l more arsenic, and this is in addition to statistically elevated arsenic levels among tribal-operated utilities. We observe negative and statistically significant associations between the low-income and Black share of the service population. We attribute the negative association between arsenic levels and Black share of the service population to lower levels of arsenic in Eastern and Southeastern states, which can be seen in Figure 6(a). In contrast to some of the other measures of drinking water quality, for arsenic we observe that the smallest systems and especially groundwater systems are the most likely to have elevated levels. On average, a ground-water sourcing system has 0.3 ug/l more arsenic than a surface-water sourcing system, and a very small system has 0.14 ug/l higher levels of arsenic.

Nitrate Concentrations (2006-2019): As shown in Table 1, the average concentration of nitrate in all community water systems from 2006-2019 is generally stable across service area boundary representations, ranging from 0.8 to 0.95 mg/l.[47] The averages are nearly identical for county, EPIC, and EPA boundary types at 0.87 mg/l, but are lower for zip code boundaries at 0.82 and higher for USGS boundaries at 0.95. We also observe that around one fifth of drinking water systems never detect nitrates and thus have a concentration value of zero, whereas systems that have non-zero concentrations have concentrations around 1.1 mg/l (see Appendix Table A4). For context, the legally enforceable limit for nitrates in drinking water is 10 mg/l.

We summarize average nitrate concentrations experienced by each demographic group in Table 2, and we illustrate disparities across these groups in Figure 7(b). Asian, Hispanic, and Pacific Islander populations are served by drinking water systems with elevated nitrate concentrations in comparison to the non-Hispanic White population. These disparities can be observed across all service area boundary types, although the magnitude of the disparaty for each group tends to be lower when using imprecise (e.g., county) or incomplete (e.g., USGS) boundary data. For American Indian communities, the prevalence of nitrates is roughly equal to the comparison group, with disparity measures both just above and just below one depending on the service area boundary type. We map nitrate concentrations in Figure 7(a), illustrating that nitrate tends to be detected at higher concentrations in the Midwestern states of Nebraska, Kansas, Oklahoma, and Texas. We also see areas with higher levels of nitrates in eastern Pennsylvania, parts of California, Idaho, Iowa, and Wisconsin. We illustrate nitrate concentrations in combination with % people of color in Figure 14(a) and % low income in Figure 14(b). These maps suggest potential hotspots for nitrate exposures to people of color in California and Texas. Clusters of low-income individuals and elevated nitrate levels can be observed in the same regions as well as a large stretch of Midwestern states such as Nebraska.

In regression analysis of nitrates in drinking water, presented in column (7) of Table 4, we show that Asian and Hispanic populations have statistically significantly elevated nitrate levels when conditioning on other water system characteristics. A ten percentage point increase in the Hispanic share of a service population is associated with 0.15 mg/l higher nitrate levels, and a similar shift in the share of a service population that is Asian is associated with 0.2 mg/l higher nitrate levels. Nitrate levels are negative and statistically significantly associated with the share of a service population that is Black. We do not observe statistically significant differences in nitrate levels for American Indian, Pacific Islander, or low-income individuals. Regarding system characteristics, we find that small and very small systems as well as groundwater systems are more likely to have higher nitrate levels.

[47] Note as described in Section 3 that for some systems we use combined nitrate and nitrite concentrations if the system does not separately report nitrate.

5.2 Supplemental Analysis

In this section, we describe national and sub-national analyses that further elucidate the differences between boundaries and how these differences might impact our conclusions. We begin by analyzing why factors such as boundary precision and data completeness affect the analytic conclusions we derive overall. We then show the significance of modelling techniques with a case study comparison of the geographic extent of health-based violations in Oklahoma according to EPIC and EPA boundaries. Finally, we conduct a series of additional state-level analyses to zoom in on within-state heterogeneity in both water quality and demographics, emphasizing the importance of precise boundaries for depicting environmental justice hotspots.

5.2.1 Larger, Less-Precise Boundaries Bias Estimated Demographic Percentages

Use of large and imprecise areas such as counties may introduce bias in estimating water system demographic information. While county representations are more complete than zip codes and usually include most if not all of the actual service area within their boundary, they also assign geographic areas to a system that are not actually served by that system. To the extent that non-served areas differ from served areas within a county, county boundaries can lead to inaccurate characterization of minority or low-income populations. Figure 15 provides scatterplot evidence on how the estimated percent minority population differs between EPA ORD boundaries and the other four boundary representations. In the top left quadrant, we observe that use of county boundaries displays the greatest statistical noise of all boundary representations. In particular, water systems serving less than 50% people of color according to the EPA ORD boundaries are frequently estimated to have much higher percentages of people of color served. Conversely, where the EPA ORD boundaries suggest a system serves at least 50% people of color, county boundaries frequently suggest much lower percentages of this demographic group. These findings can be seen in the large mass of observations well above the line of 45 degrees where the EPA ORD percent minority is less than 50%. Similarly, where the EPA ORD percent minority is greater than 50%, there are many dispersed observations below the line of 45 degrees where use of county boundaries under-estimates the minority share of a service population. In Figure 16, we provide similar evidence with respect to percent low-income, again demonstrating that county boundaries tend to have the greatest degree of statistical noise. We also display these scatter plots for all minority populations in Appendix Figure A3 to Figure A7. In these plots, we observe the greatest noise for groups that constitute a lower share of the general population such as American Indian and Pacific Islander populations.

5.2.2 Data Completeness Affects Analytic Conclusions

As further demonstration of the differences between service area boundary types, we create two maps comparing the number of health-based violations that would be missed when using zip code or USGS boundaries, which notably do not capture all community water systems, in Figure 17(a) and Figure 17(b). These maps convey that a large number of violations and communities would not be captured in an analysis that only relied on these boundaries. In addition, many of the violations that would be missing are in areas that tend to have greater numbers of health-based violations such as Western Texas and Oklahoma. Such a finding helps to explain why we observe lower disparities with respect to health-based violations when using USGS and zip code boundaries, and it underscores that data completeness can impact the results of an environmental justice analysis of drinking water quality.

5.2.3 Boundary Modelling Decisions Are Consequential

To help illustrate how different methods for approximating service area boundaries can lead to different conclusions with respect to environmental justice concerns, we produce bivariate maps of the count of health-based violations and percent people of color in Oklahoma using the EPIC and EPA ORD boundaries. We choose Oklahoma for a case study of health-based violations because it has a high number of health-based violations, and a large share of the population is American Indian, which we note to be an important disparity in this particular metric. Furthermore, this is a state that does not have state pre-supplied boundaries, and therefore allows us to show how boundary modelling techniques can thus lead us to different environmental justice conclusions. This case study therefore sheds some light on the heightened prevalence of health-based violations for American Indian populations described above. In this case study, each boundary data source relies on distinct modeling methods for boundaries in the absence of state-provided data, where EPIC's methods primarily rely on municipality boundaries or centroid buffers (i.e., tier 2 and tier 3) while the EPA ORD boundaries use a multi-step procedure described above. We note a few differences between the modeled boundaries. First, there are a different number of systems in the EPA-ORD (745) and EPIC (899) boundary data, which will impact the overall number of violations and their spatial extent. Second, the EPA-ORD boundaries are generally smaller and more precise than the EPIC boundaries, which tend to be larger and sometimes overlapping polygons. When spatially interpolating the boundaries onto census block-groups, the EPA ORD boundaries therefore include fewer census divisions for any given water system, which tends to lower the estimated number of violations in many census block groups. In addition, the EPIC boundaries tend to have more overlapping systems, which can have an ambiguous impact on any particular census block group's perceived water quality depending on whether incorrectly overlapped service areas have more or less violations. This pattern quite dramatically affects where an analyst might locate environmental justice hotspots in the state; with the EPIC boundaries, much of the Southeastern corner appears to have many violations and a high percentage of people of color. The EPA boundaries show these hotspots with more geographic precision.

5.2.4 Insights from State-Level Bivariate Maps

We also produce state-level bivariate maps for selected drinking water quality indicators to visually demonstrate the value in using precise service area boundary representations in characterizing environmental justice hotspots, or locations with drinking water quality concerns and heightened socioeconomic vulnerability. State-level analyses can help to portray local disparities in drinking water quality, especially in densely-populated areas, and help motivate the use of precise boundary tools and census measures when considering areas with potentially concentrated environmental justice concerns. We focus on these states mostly to show the level of precision that is hard to view when considering national maps at this spatial scale.[48] To start, we map the historical presence of lead action level exceedances in Ohio (Figure 19(a)). Ohio had some of the highest number of lead action level exceedances across all states, and Hamilton County, which encompasses Cincinnati, had some of the highest number of lead action level exceedances and percent people of color in the state. Next, since certain states have sampled for PFAS more completely and frequently, we zoom in on New Jersey in Figure 19(b). New Jersey has samples for these chemicals across all of its systems, and the state's water systems had many detections of PFAS in its systems across the study period. We note several areas where we see both more types of PFAS detected in its water systems and higher population of color, such as in the Essex region in the northeast. Finally, we highlight DBP levels in North Carolina in Figure 19(c), which has several regions where high overall concentrations also intersect with relatively high proportion of people of color.

5.2.5 Drinking Water Quality Concerns Co-Occur with Other Environmental Burdens

We test whether drinking water quality measures are are associated with other measures of environmental burden in Table A6.[49] In this table, each column conveys correlations between a given drinking water measure and the measures of environmental burden in each row. To start with the lead indicator in EJSCREEN, which represents the share of houses built prior to 1960, we observe that health-based violations, lead

[48] For national versions of these maps, see Figure 8(a), where we display a series of national bivariate maps for both people of color and low-income populations.

[49] We source measures of environmental burden from EJSCREEN 2.0 and include only a subset of all environmental indicators because many indicators are likely highly correlated with each other (e.g., diesel particulate matter, traffic proximity, and PM 2.5). We also exclude certain indicators that present a challenge to interpretability of regression coefficients, such as the air toxics respiratory hazard index.

ALEs, DBPs, and nitrate levels are statistically significantly associated with greater lead paint hazards. This suggests that communities with older housing stocks not only have a greater likelihood of lead paint exposure but are also more likely to be served by water systems with more lead action level exceedances, health-based SDWA violations, DBPs, and nitrates. Both measures relating to air pollution, Ozone and PM 2.5, are associated with more health-based SDWA violations as well as nitrates nitrates. We see mixed results across PM 2.5 and Ozone for lead ALEs, PFAS, total coliform detection, and arsenic. Proximity to hazardous waste treatment, storage, and disposal facilities is positively associated with more lead action level exceedances, PFAS, DBPs, total coliform detections, and nitrates. However, these hazardous waste sites are associated with fewer health-based SDWA violations and lower arsenic levels. Superfund site proximity is significantly associated with more lead ALEs, nitrates, and PFAS levels. The association between Superfund proximity and PFAS concentrations is the largest relationships in magnitude that we observe with respect to PFAS. Finally, we note with interest that wastewater discharge, the only water-based pollutant indicator in EJSCREEN, is negatively associated with health-based violations and lead action level exceedances and not statistically significantly associated with any of the other drinking water quality indicators.[50]

5.2.6 Geospatial Aggregation Methods Can Mute the Extent of Disparities

We conclude this section by showing how data aggregation methods can suggest different extents of variation in water quality. While this exercise does not convey differences across types of service area boundaries, it is relevant to the production of visualizations using service area boundaries. We generate a set of maps of health-based violation frequency in New Jersey across census designations with different levels of spatial granularity in Figure 2(a) to Figure 2(c).[51] Notably, average health-based violation counts at the tract and county levels tend to show less variation across areas than maps at the CBG-level. For example, the counties with the greatest number of health-based violations have only 10 on average, while it is clear that certain areas have many more than ten health-based SDWA violations when employing census block groups or tracts. However, this reduction in variation when using counties comes with trade-off that all areas have at least one observed value. The other maps have certain white areas with no water systems and hence no health-based violations. These gaps in spatial coverage are likely areas where most residents use private domestic wells.

[50]For more discussion on the water-related environmental risk factors, see Scanlon et al. (2023).

[51]New Jersey has high-quality service area boundaries produced by the state, rendering the analysis more spatially reliable.

5.3 Sensitivity Analyses

We conduct a battery of sensitivity tests relating to different subsets of water systems, types of drinking water quality measures, and regulatory periods over which the measures are constructed.

First, we test the sensitivity of our results to alternative subsets of water systems and their associated boundaries. The results of these sensitivity tests are displayed in Appendix Table A1, Table A2, and Table A3. The first analysis subsets to water systems with service area boundaries listed as tier 1 or tier 2 in the EPIC boundaries, while Table A2 subsets to EPIC tier 2 and tier 3 systems. In both cases, the purpose of these sensitivity tests is to determine whether our conclusions tend to be driven by modelling techniques for systems without publicly-available boundary data. Of course, using a different subset of states or systems is also expected to alter the underlying disparity measures irrespective of boundary accuracy, and so we therefore focus primarily not on the altered magnitude of disparities but on the relative differences across boundary representations. Next, because some states with tier 1 boundaries also have questionable accuracy, we perform this subset analysis with respect to five states that have more accurate service area boundary data in Appendix Table A3. These states are California, Connecticut, New Jersey, New Mexico, and Washington. In all subgroup analyses, we observe qualitatively similar results suggesting that geospatial methods for boundary aggregation can affect the results of an environmental justice analysis. We observe much more variation in conclusions where modelling approaches differ (e.g., EPIC tier 2 and tier 3 data).

Next, our PFAS measure could present biased disparity measures due to differential sampling behaviors across systems and changing detection thresholds over time. We therefore present four alternative drinking water quality measures for PFAS: the sum of the maximum concentration of each distinct PFAS sampled, which emphasizes the tails of the PFAS concentration distribution (see Appendix Figure 8(a)); the PFAS detection share (see Appendix Figure 8(b)); the count of unique PFAS ever detected, which is less prone to bias from differing detection thresholds over time (see Appendix Figure 8(c)); and the sum of just PFOA and PFOS, which are the most frequently sampled PFAS (see Appendix Figure 8(d)). We also produce disparity measures for the total number of PFAS samples collected by demographic group, which sheds light on whether certain groups are less likely to have had PFAS sampled in their drinking water (see Appendix Figure A10). In general, we find that the same population groups (i.e., Asian, Black, and Hispanic) are served by systems with elevated PFAS irrespective of the specific measure employed. The count of unique PFAS detected and the detection share tend not to suggest a disparity for certain groups such as low-income populations or American Indian communities. This finding reflects that American Indian communities are not necessarily more likely to have PFAS in drinking water, but that PFAS is present at higher concentrations when it is detected. We also observe significantly more variation in findings across the service area boundary types when employing the sum of maximum PFAS concentrations measure, which we attribute to the higher degree of right skew in this measure. Finally, we show our primary disparity measure for PFAS when excluding samples collected prior to 2020, which ensures that all samples have similar detection thresholds. These results are presented in Appendix Figure A9, and they show very similar results to our primary disparity measures plotted in Figure 3(b).

We also conduct a variety of sensitivity tests related to DBPs. Different classes of DBPs tend to form under different circumstances, and so we show our primary disparity measures according to just TTHM in Appendix Figure 11(a) and just HAA5 in Figure 11(b). When separating these two DBP classes, we find very similar results to the primary disparity measures shown in Figure 4(b). For all service area boundary types, we observe disparity measures less than one for Hispanic and Pacific Islander populations and disparity measures greater than one for Black and low-income populations across TTHM, HAA5, and the combined sum of the two. For Asian populations, disparity measures are both above and below one across TTHM, HAA5, and the combined sum of each; USGS and county boundaries suggest heightened risk for all three DBP measures, while other boundary types suggest lower risk. We observe very minor differences in disparity measures for American Indian populations with respect to TTHM and one service area boundary type. For American Indian populations, we see a potential disparity in TTHM levels according to only the USGS houndaries, while we do not observe this potential disparity with respect to HAA5 or the combined sum of both classes.

Finally, we show results how disparity measures may differ when subsetting to samples collected over periods with different regulatory requirements. We start by showing DBP disparity measures exclusively for the Six Year Review 3 in Appendix Figure 12(a) and for the Six Year Review 4 in Appendix Figure 12(b). When limiting to later years, results are nearly identical to those of the pooled sample. However, when limiting samples to pre-2013 data, we see higher disparity measures for American Indian and Hispanic populations according to one and two boundary types, respectively. We perform the same exercise with total coliform samples collected prior to and after a regulatory change was implemented in 2016 in Appendix Figure 13(a) and Figure 13(b). For total coliform, we again observe nearly identical results over either regulatory time horizon. In all alternative sample horizons, we conclude that limiting the analysis to only the most-recent samples would not change our conclusions regarding disparities. Moreover, we draw the same conclusions regarding the extent to which conclusions can vary across less-refined and more geospatially precise service area boundaries.

5.4 Limitations

Several limitations apply to this analysis. First, regarding the maps, the averaging of water quality indicators for all systems serving a census division means that the mapped values may not precisely represent the water quality experienced by a particular household in a given block group. Related to this point, we do not generally observe tap-level concentrations of the contaminants informing our drinking water quality measures, and samples taken at a treatment plant or at specific nodes within a distribution network may under-estimate average tap-level concentrations of certain contaminants.[52] Second, the unique nature of each drinking water quality indicator results in varying extents of geospatial heterogeneity and missing observations across communities. For example, we lack any PFAS samples for large stretches of the United States. Third, drinking water indicators represent average impacts over a relatively long period of time and may not necessarily reflect current conditions in certain areas or for particular systems. While we can rule out that the time period of our sampling data changes our results for PFAS and total coliform detection rates, we do observe some minor differences for certain groups with respect to earlier DBP samples. We leave analysis of temporal trends of disparities in these drinking water measures to future work.

6 Conclusion

In this paper, we explore how the choice of representation of service area boundaries for community drinking water systems can impact the results for environmental justice analyses. We do so by collecting all known service area boundary types, and we then compare a novel set of novel drinking water quality metrics across the various boundary types. We also conduct correlational regression analyses to understand how measures of drinking water quality are correlated with water system and community characteristics. Our findings demonstrate that the results of EJ analyses can be sensitive to modelling decisions with respect to water system service areas. Moreover, whether a finding of a disparaty is sensitive to the choice of service area often depends on the type of water quality metric under study. These results highlight the necessity of collecting water system service areas across all public water systems and maintaining their accuracy over time. These findings also underscore the importance of employing a consistent set of service areas across environmental justice analyses.

Our study points to several avenues for future work on this topic. For instance, the importance of collecting and updating high quality service area boundary data raises the need to evaluate the accuracy of different types of boundaries. In this paper, we intentionally avoid comparing the accuracy of the various boundary representations and focus on the comparison of conclusions when making different assumptions about the

[52] For more discussion of contaminant formation within distribution networks, see EPA (2002b).

geospatial extent of service area boundaries. Future research can evaluate the accuracy of both estimated boundaries as well as publicly available boundaries provided by states to help inform which boundary types lead to the most accurate policy analysis or other research. Additional research on environmental justice in drinking water could potentially help this process. For example, it would be valuable to assess environmental justice concerns in states or regions that have been studied less in the prior literature, which often focuses on states with available boundary data.

In addition, while we explore some of the disparities in drinking water quality across demographic groups and geographic regions, certain findings require further exploration. For one, research could delve further into the causes of disparate drinking water quality such as differential infrastructure maintenance, the legacy redlining on public service provision, or uneven geospatial distribution of populations near anthropogenic and geogenic sources of pollution. Such research could also more carefully document the joint distribution of income, race, and drinking water quality. Further exploration of drinking water quality hotspots or regional differences could also provide more context for studies at the national level, helping to refine research questions as well as hone in on the consequences of lower drinking water quality like public health and water affordability concerns.

Finally, this analysis explores how socioeconomic indicators of underlying vulnerability relate to drinking water quality, but researchers could expand this analysis to include differences in other metrics associated with vulnerability such as public health outcomes and water affordability. Researchers could expand analysis of environmental justice concerns in drinking water to additional contaminants or types of drinking water quality indicators. Similarly, there is room for additional work exploring the sensitivity of results to different formulations of these drinking water indicators, such as for example the creation of drinking water indexes that combine information across several metrics.

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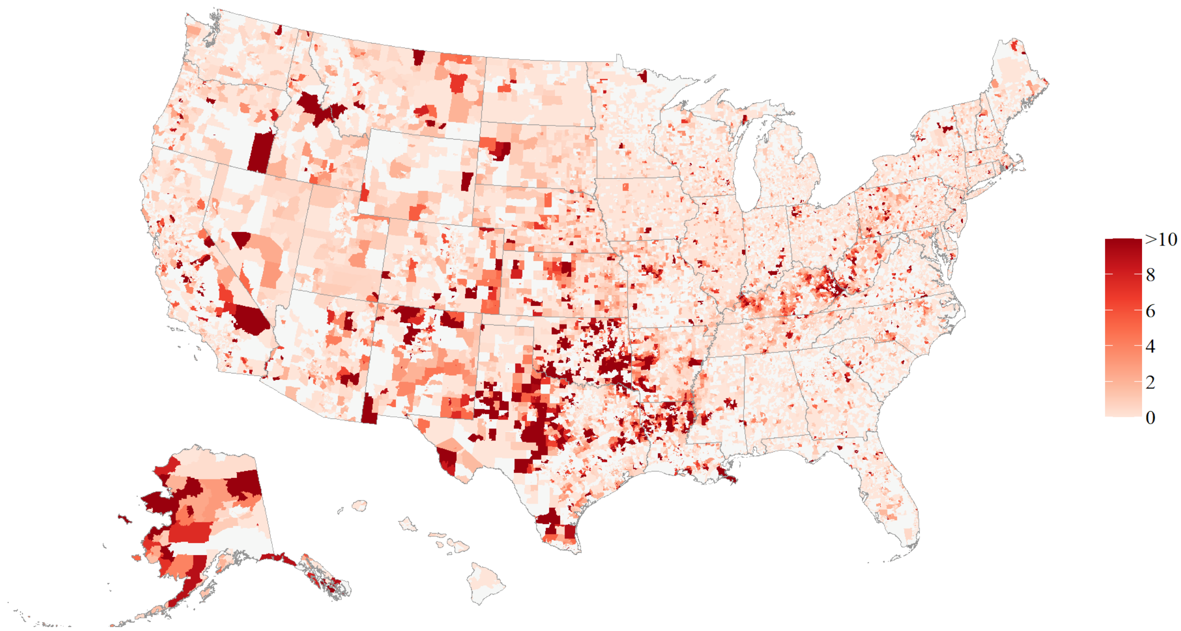
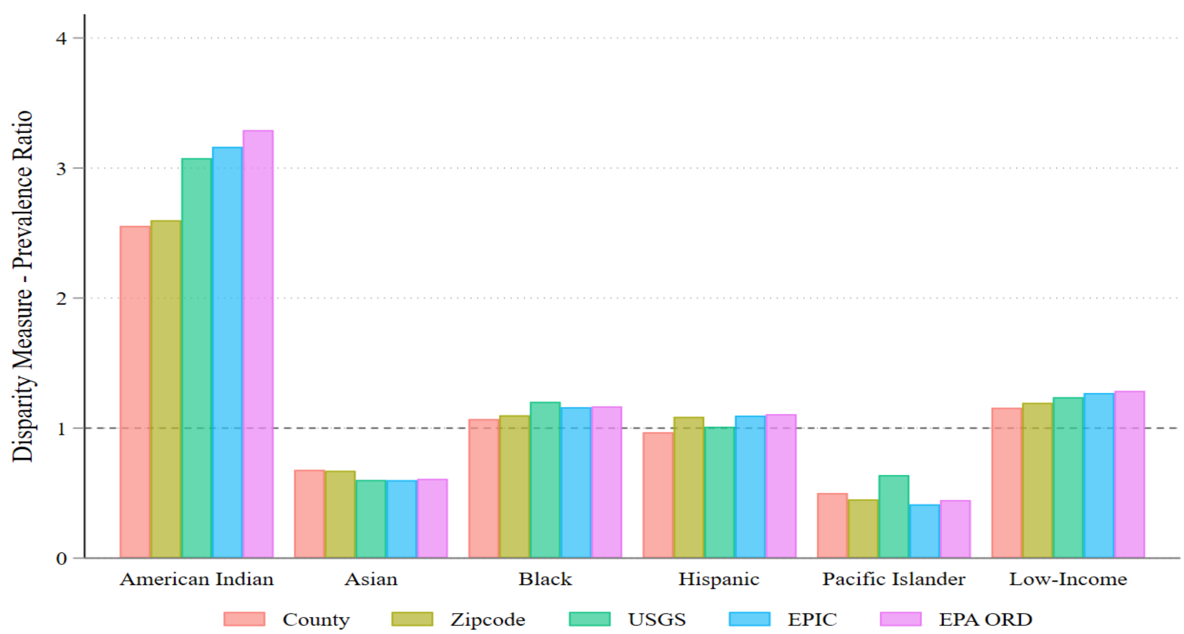
Figures

Figure 1: Health-based Violations of the Safe Drinking Water Act (2015-2023)



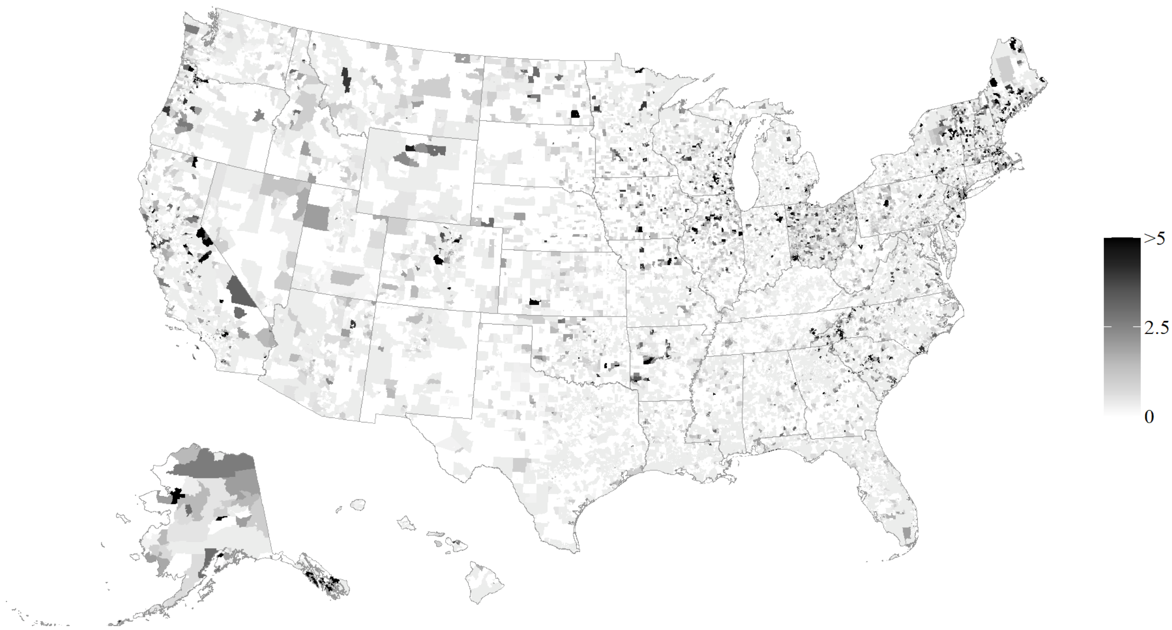
(a) Nationwide Map of Health-based Violations at the CBG Level



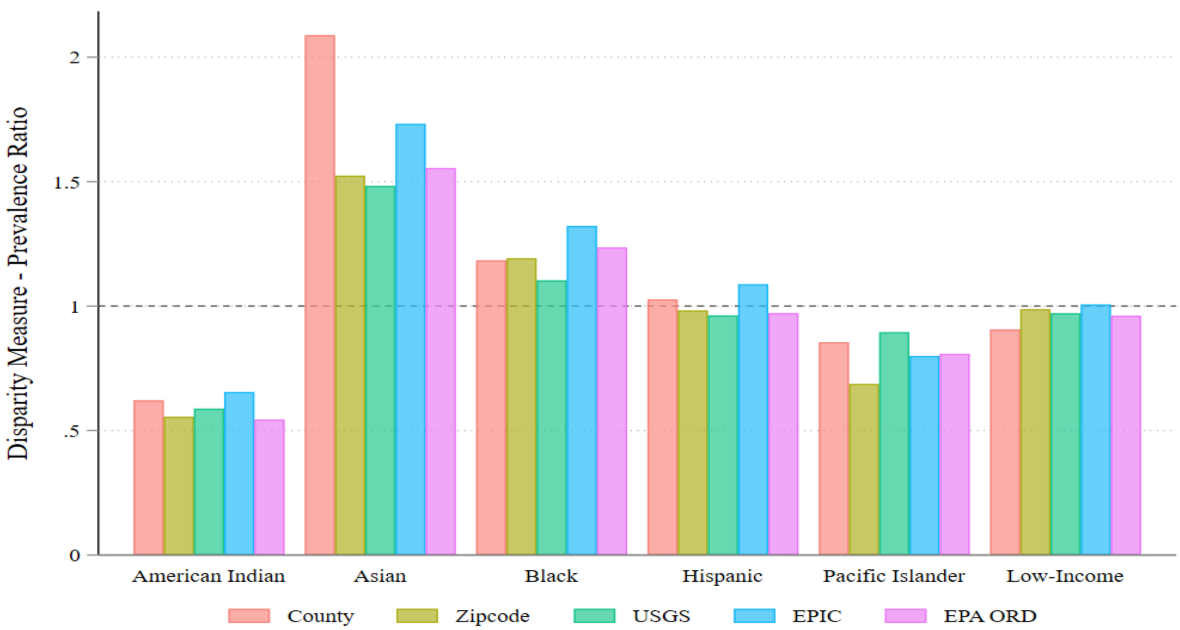
(b) Relative Prevalence of Health-Based Violations by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. Violations are averaged within CBG across all intersecting service area boundaries. Prevalence is plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Prevalence for low-income populations are plotted relative the non-low-income population.

Figure 2: Lead Action Level Exceedances (1991-2021)



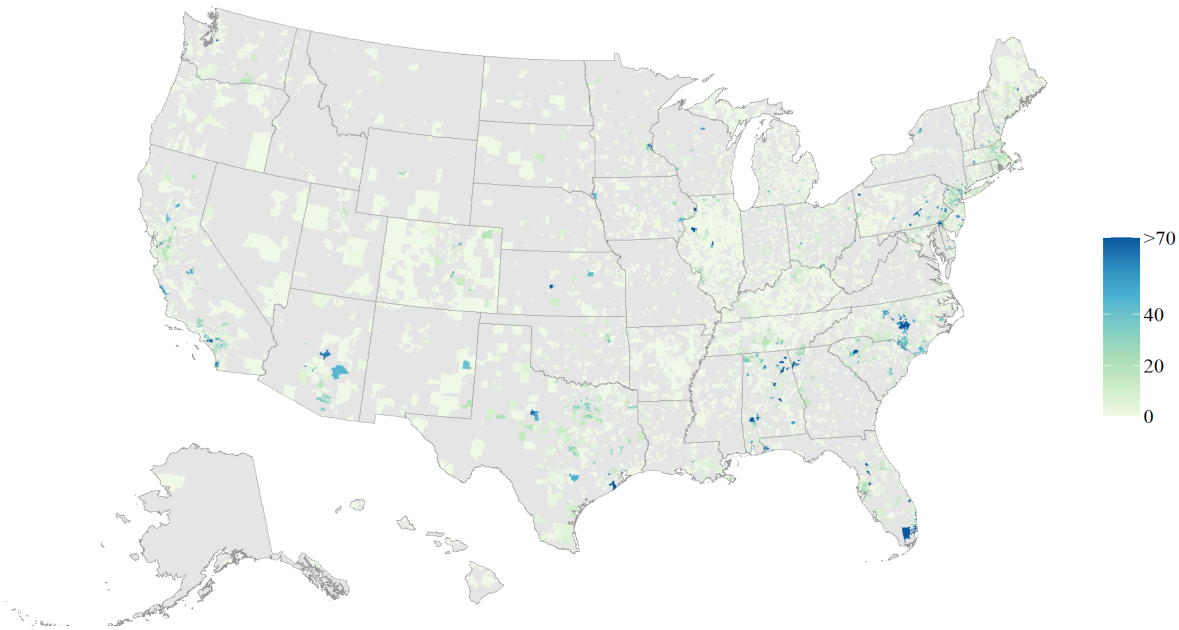
(a) Nationwide Map of Lead Action Level Exceedances



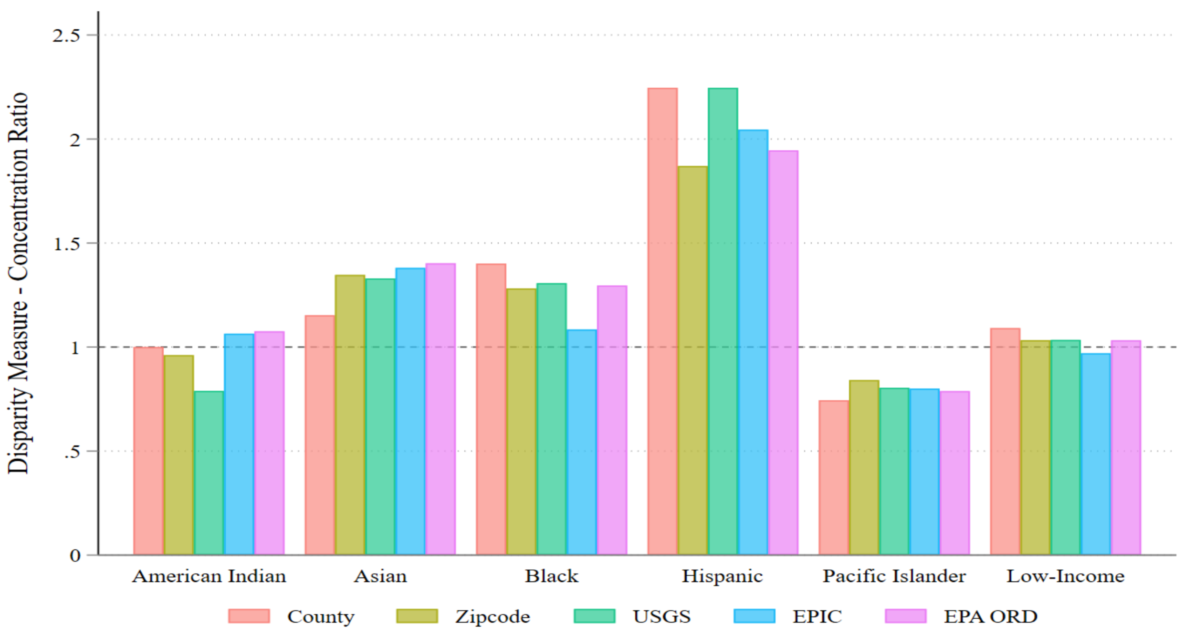
(b) Relative Prevalence of Lead Action Level Exceedances by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. Lead action level exceedances are averaged within CBG across all intersecting service area boundaries. Prevalence is plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Prevalence for low-income populations are plotted relative the non-low-income population.

Figure 3: Total PFAS Concentrations in ng/l (2013-2023)



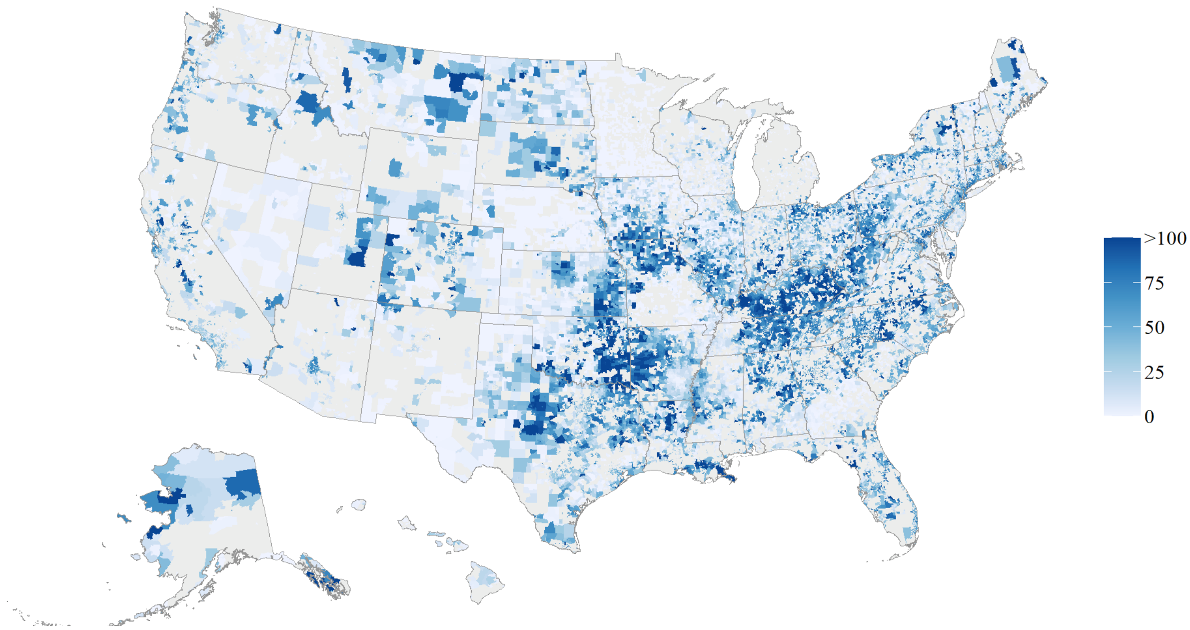
(a) Nationwide Map of Total PFAS Concentrations



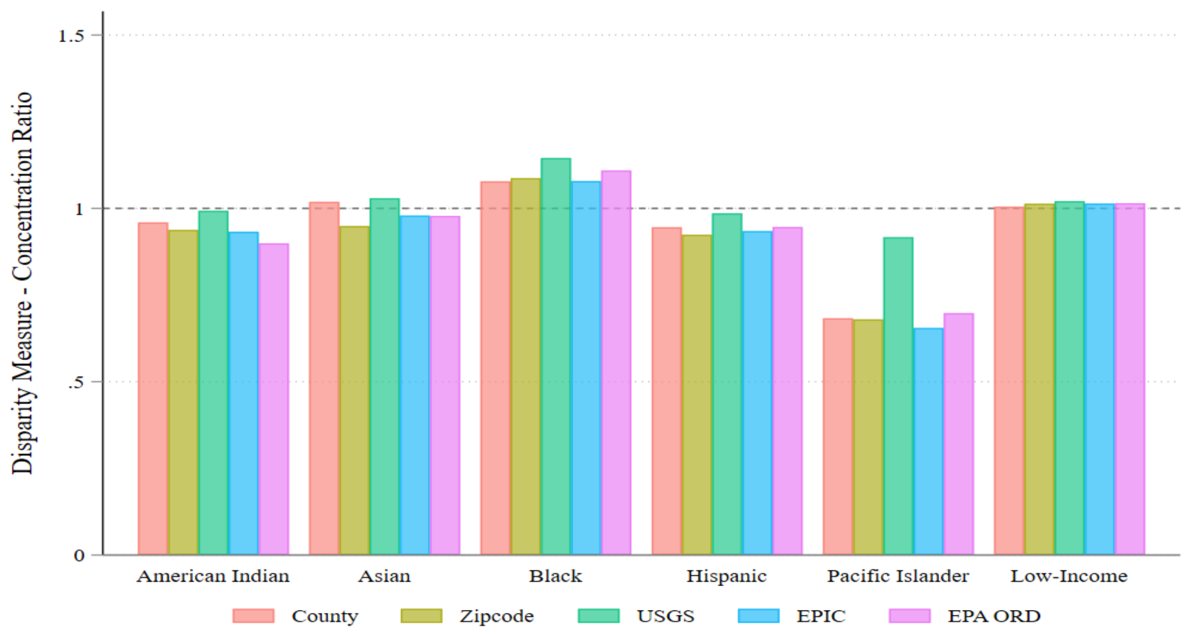
(b) PFAS Disparity Measures by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. PFAS concentrations are averaged within each PFAS species and then summed across all PFAS for a given system. These system-level total concentrations are averaged within CBG across all intersecting service area boundaries. Total concentrations are plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Concentrations for low-income populations are plotted relative the non-low-income population.

Figure 4: Combined Disinfection Byproduct Concentrations in $\mu g/l$ (2006-2019)



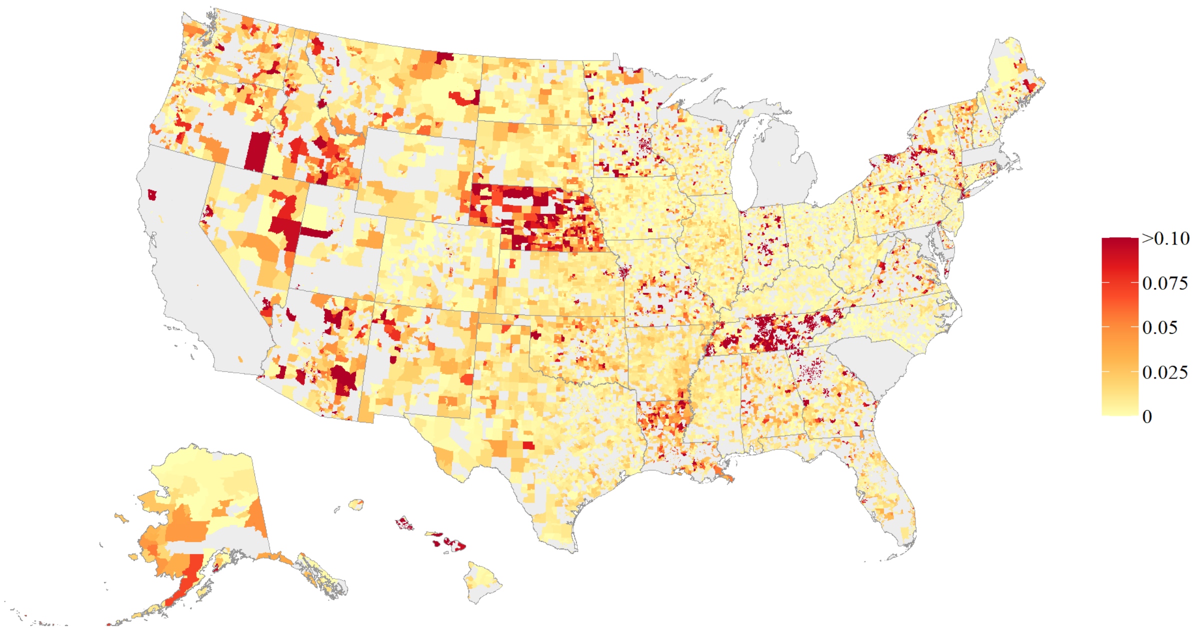
(a) Nationwide Map of Combined Disinfection Byproduct Concentrations



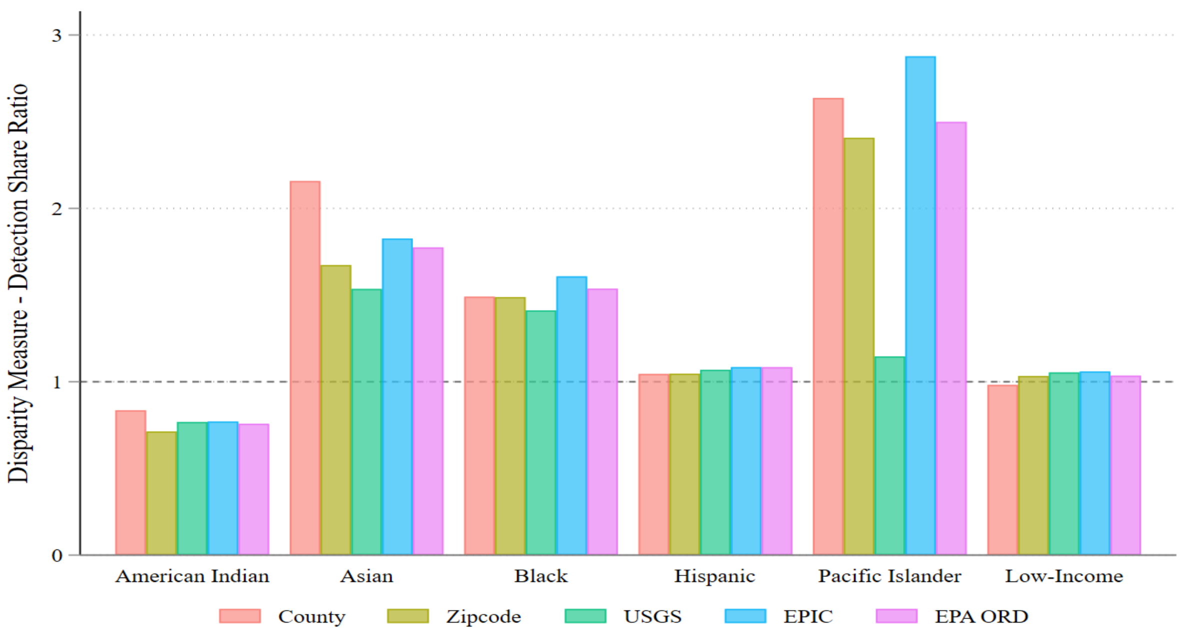
(b) Disinfection Byproduct Concentration Ratios by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. DBP concentrations are the sum of the average total trihalomethane and total haloacetic acid concentrations for each system, which are then averaged within CBG across all intersecting service area boundaries. Concentration are plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Concentration for low-income populations are plotted relative the non-low-income population.

Figure 5: Total Coliform Detection Share (2006-2019)



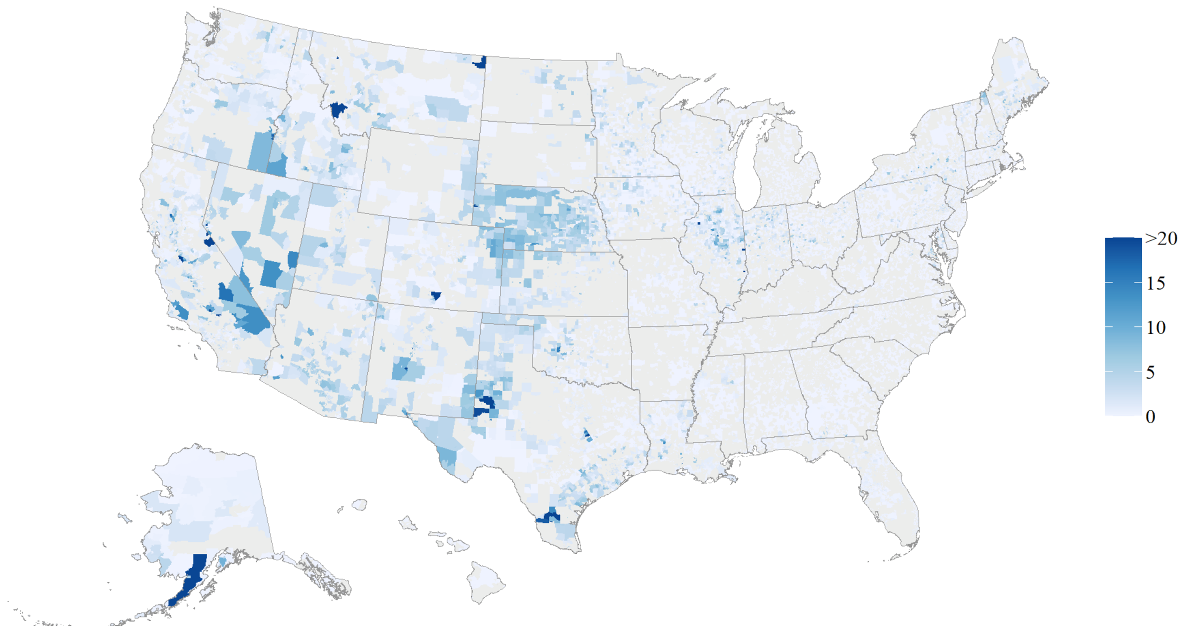
(a) Nationwide Map of Total Coliform Detections



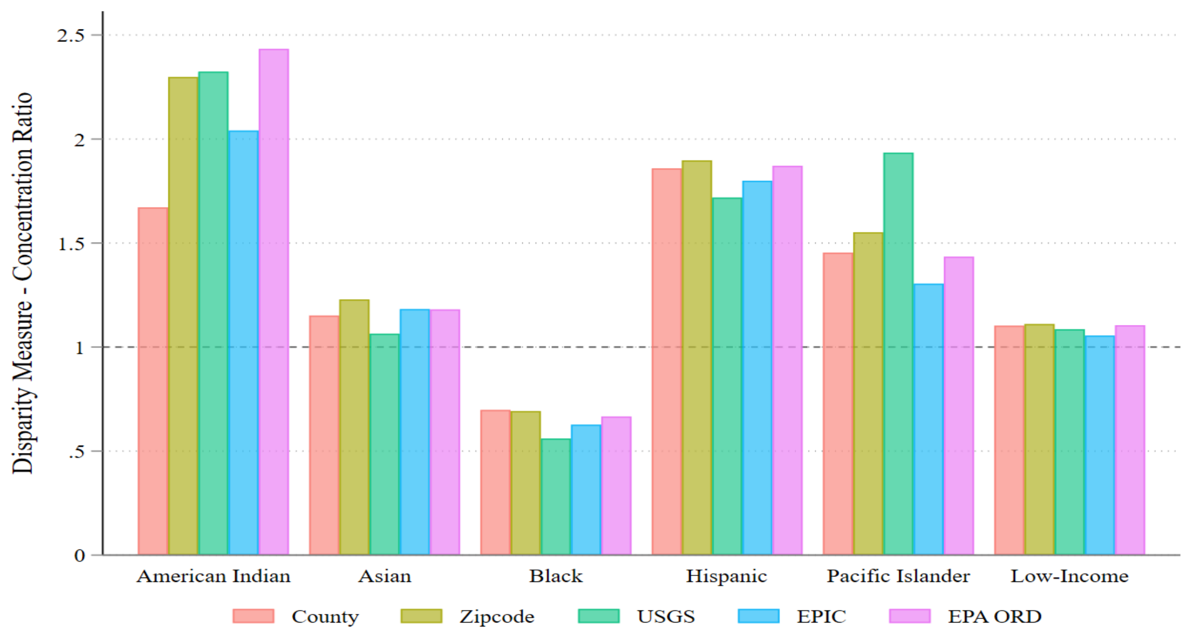
(b) Total Coliform Detection Disparity Measures by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. Total coliform detection shares are the proportion of all samples that have positive detections of these bacteria, which are averaged then within CBG across all intersecting service area boundaries. Detection shares are plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Detection shares for low-income populations are plotted relative the non-low-income population.

Figure 6: Arsenic Concentrations in $\mu g/l$ (2006-2019)



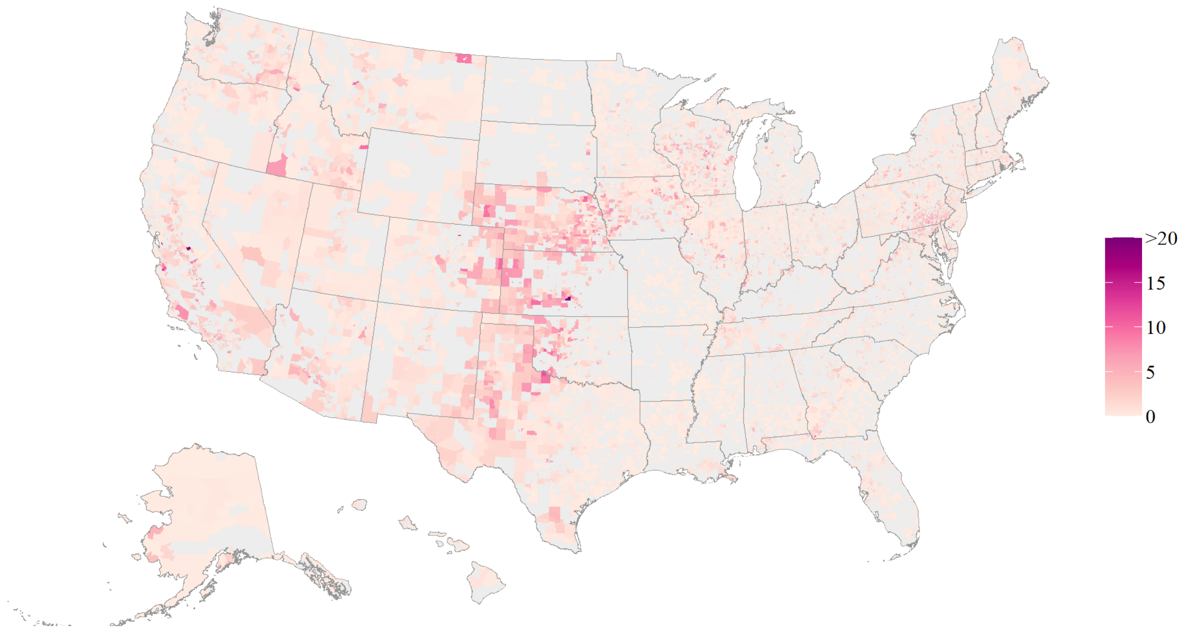
(a) Nationwide Map of Arsenic Concentrations



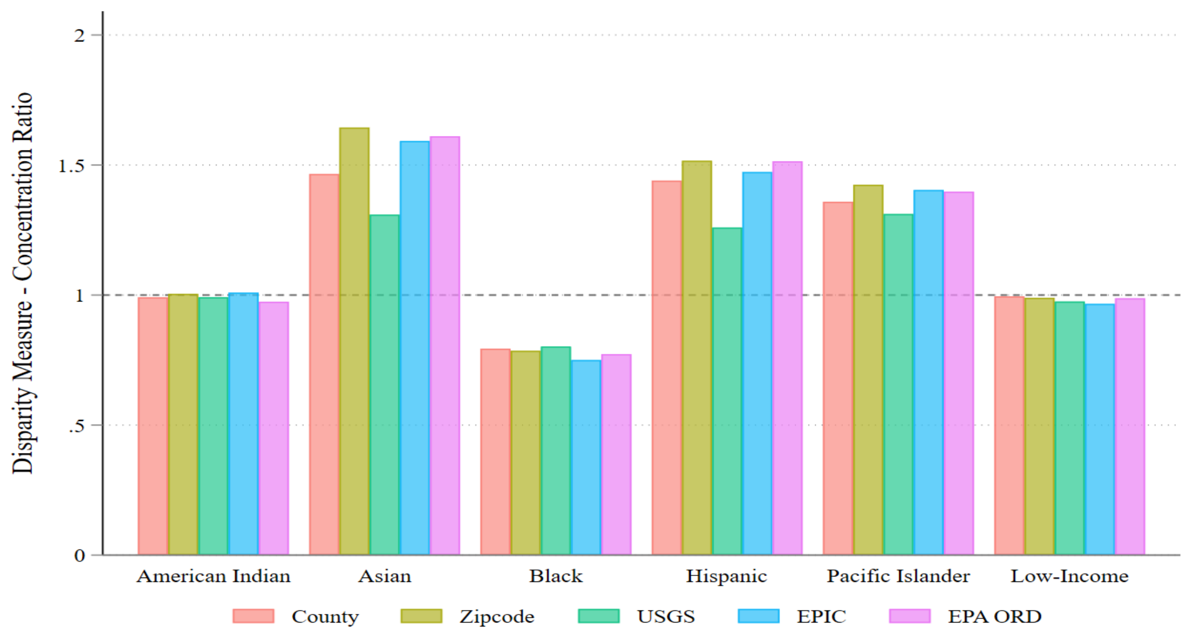
(b) Arsenic Concentration Ratio by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. Arsenic concentrations are averaged over all samples by PWS and the averaged within CBG across all intersecting service area boundaries. Concentrations are plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Concentrations for low-income populations are plotted relative the non-low-income population.

Figure 7: Nitrate Concentrations in mg/l (2006-2019)



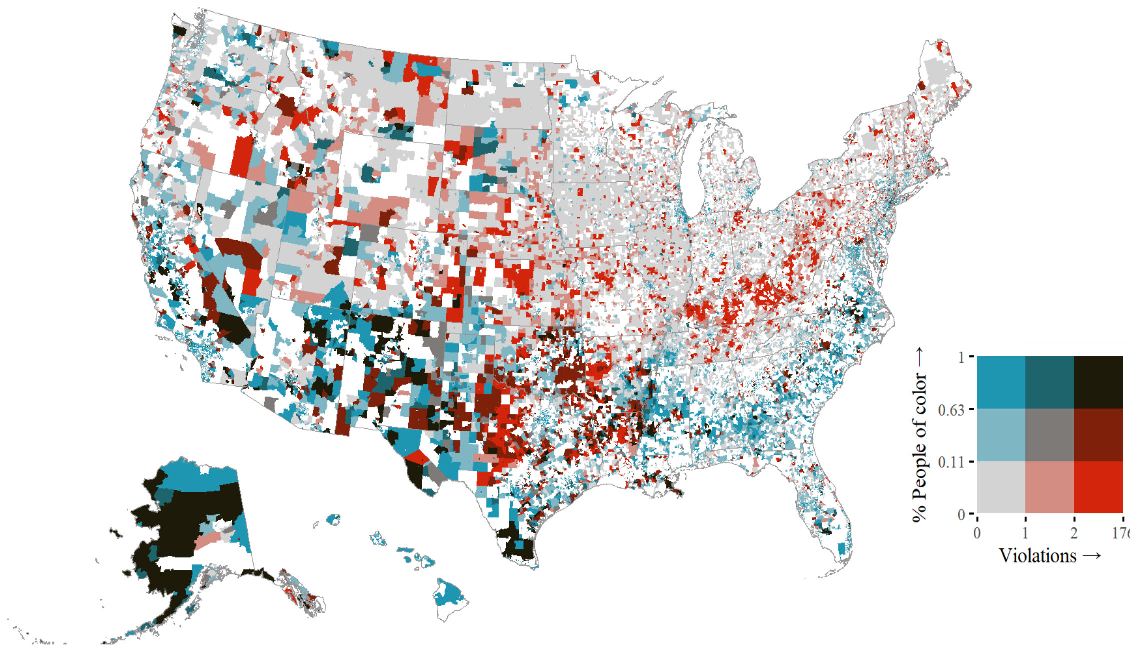
(a) Nationwide Map of Nitrate Concentrations



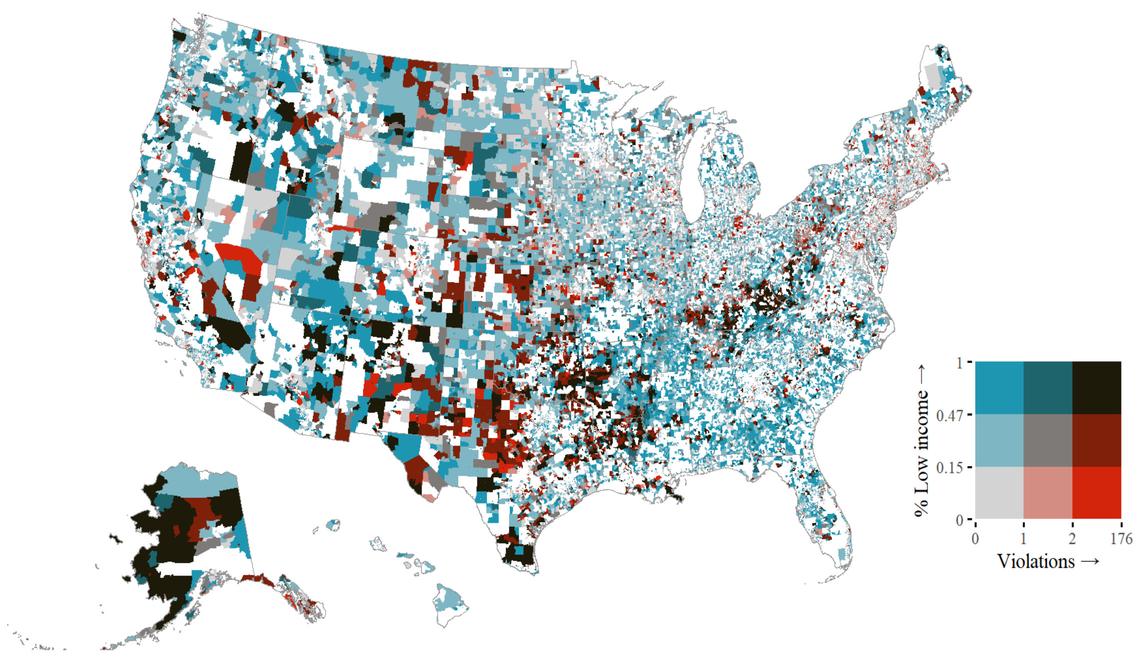
(b) Nitrate Concentration Ratio by Demographic Group

Notes: Map generated using EPA ORD service area boundaries intersected with Census Block Groups. Nitrate concentrations are averaged over all samples by PWS and the averaged within CBG across all intersecting service area boundaries. Concentration are plotted relative to the non-Hispanic White population for American Indian, Asian, Black, Hispanic, and Pacific Islander populations. Concentrations for low-income populations are plotted relative the non-low-income population.

Figure 8: Bivariate Maps of Health-Based Violations of the Safe Drinking Water Act



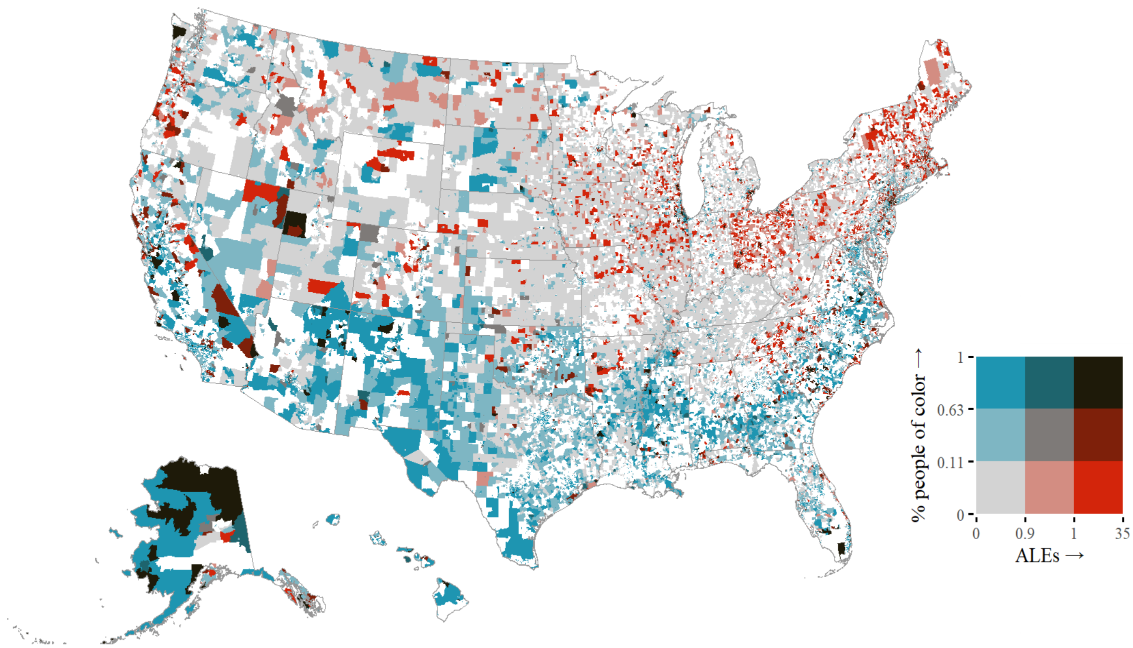
(a) Number of health-based violations and % People of Color in each Census Block Group



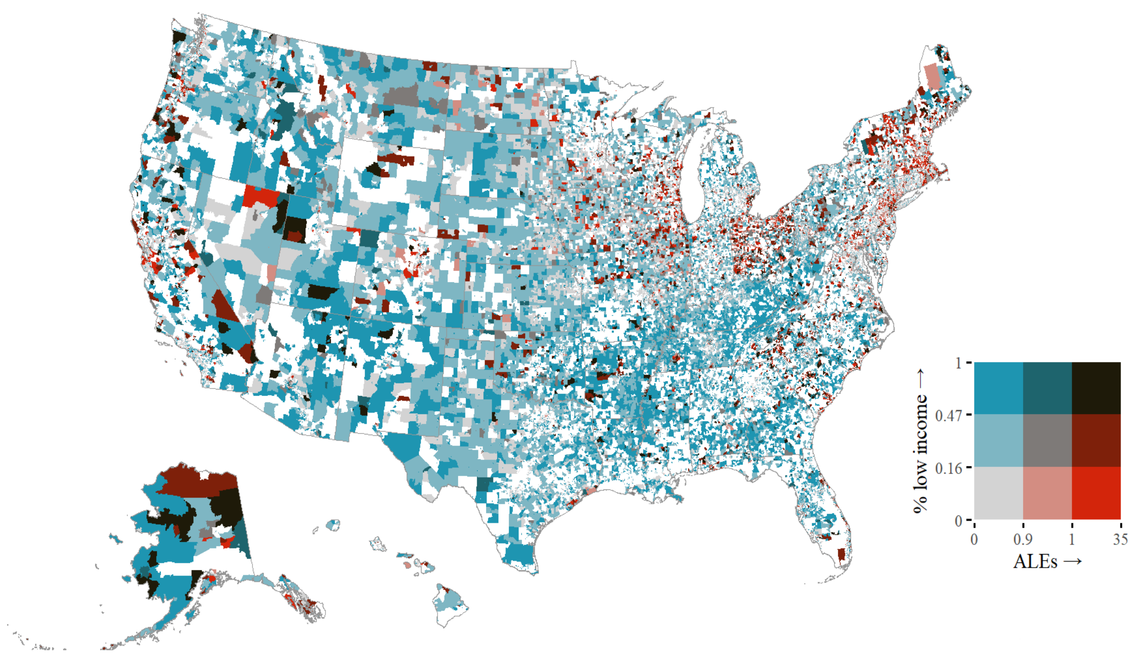
(b) Number of health based violations and % people living below 2X the Federal Poverty Level in each Census Block Group

Notes: Demographic information is based on 2021 ACS 5-year data. Health-based violations are summed over 2015-2023.

Figure 9: Bivariate Maps of Lead Action Level Exceedances of the Safe Drinking Water Act



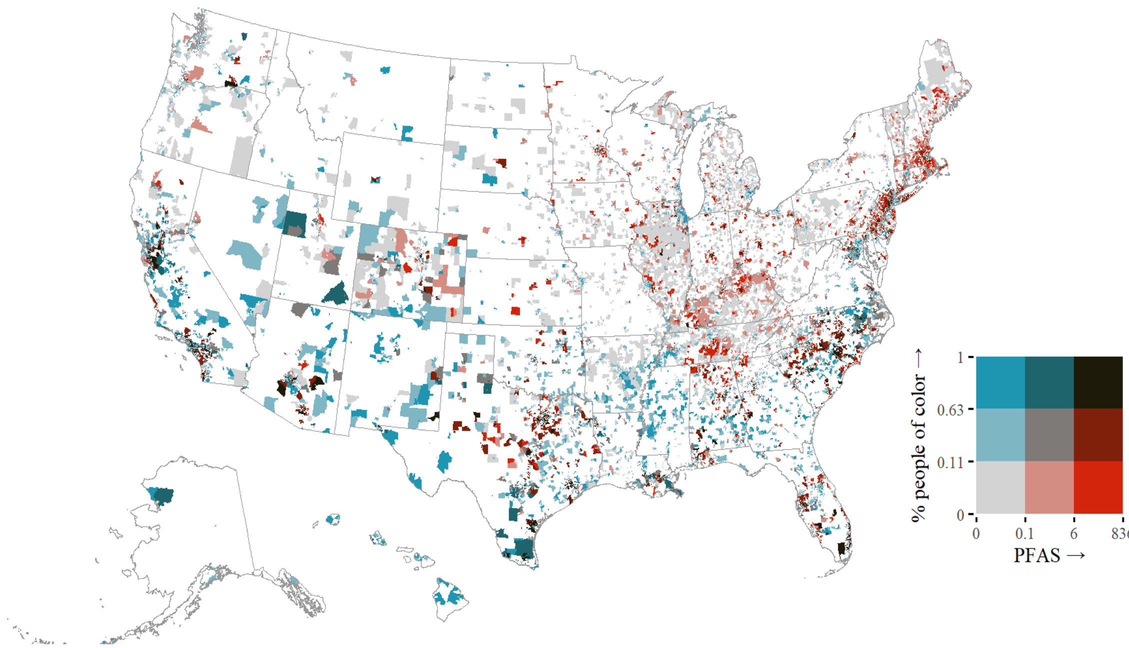
(a) Count of lead action level exceedances and % People of Color



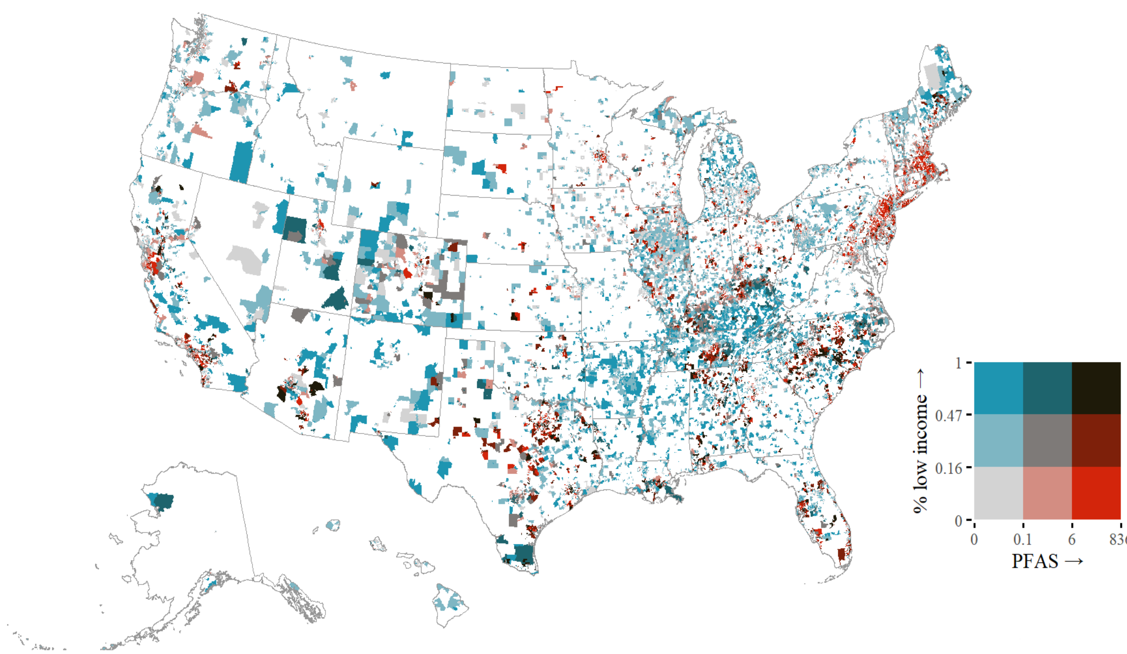
(b) Count of lead action level exceedances and % people living below 2X the Federal Poverty Level

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level. Lead action level exceedances are summed over 1991-2021.

Figure 10: Bivariate Maps of PFAS Concentrations in Drinking Water (2013-2023)



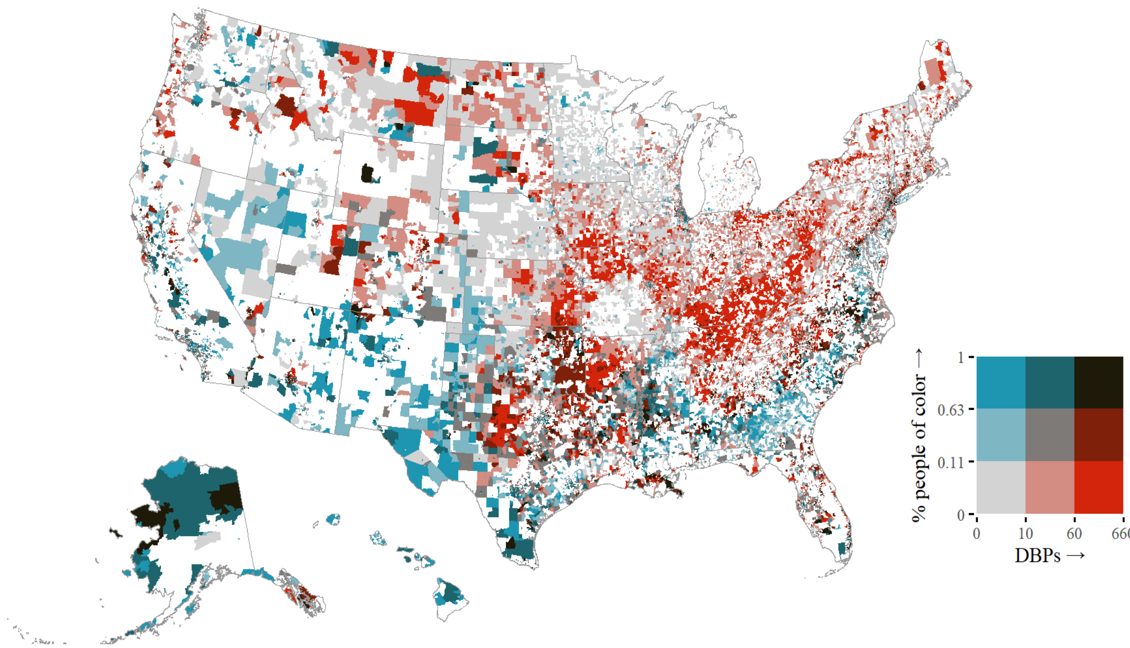
(a) PFAS Concentration and % People of Color



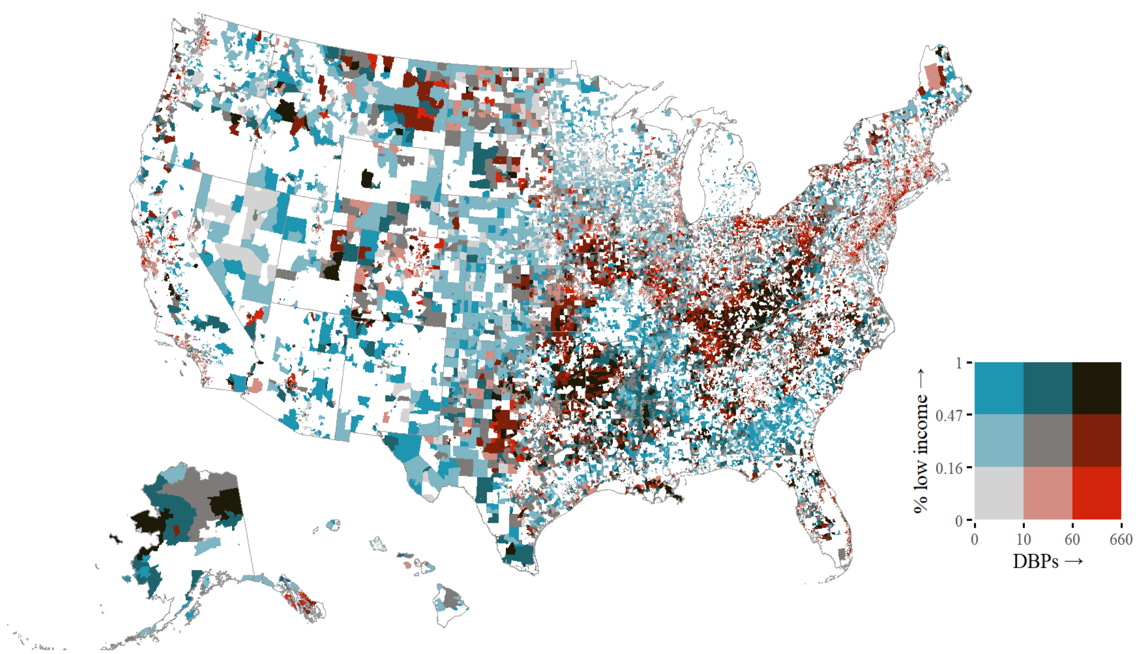
(b) PFAS Concentration and % people living below 2X the Federal Poverty Level

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level. PFAS concentrations represent average concentrations across all the CWS in one block group.

Figure 11: Bivariate Maps of DBP Concentrations (2006-2019)



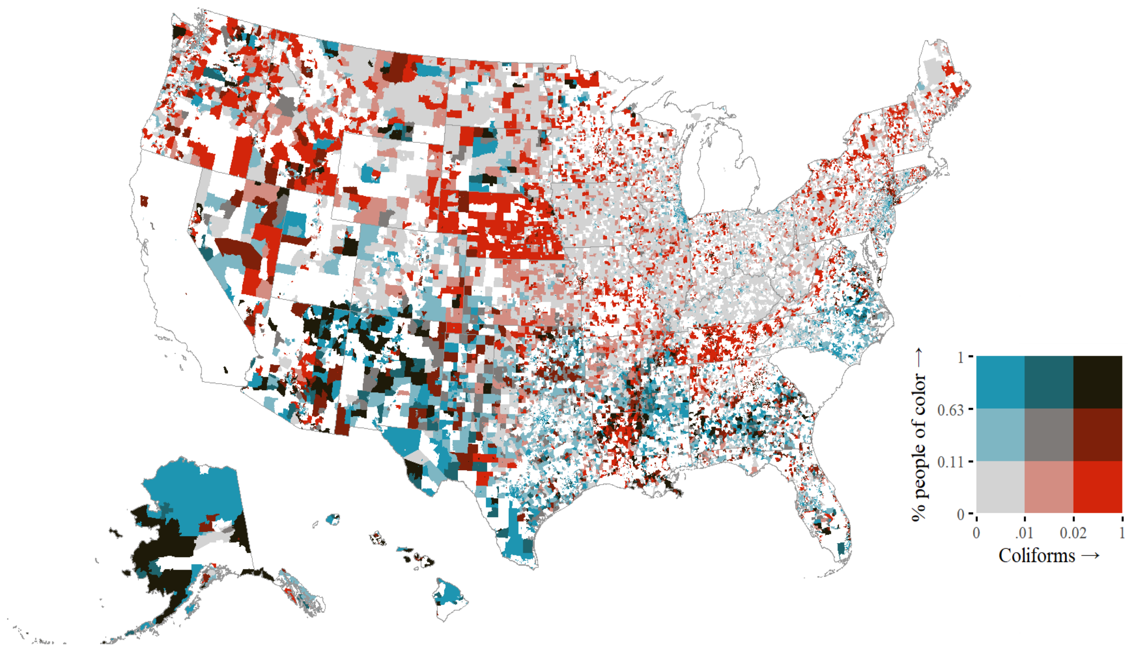
(a) DBP Concentrations and % People of Color



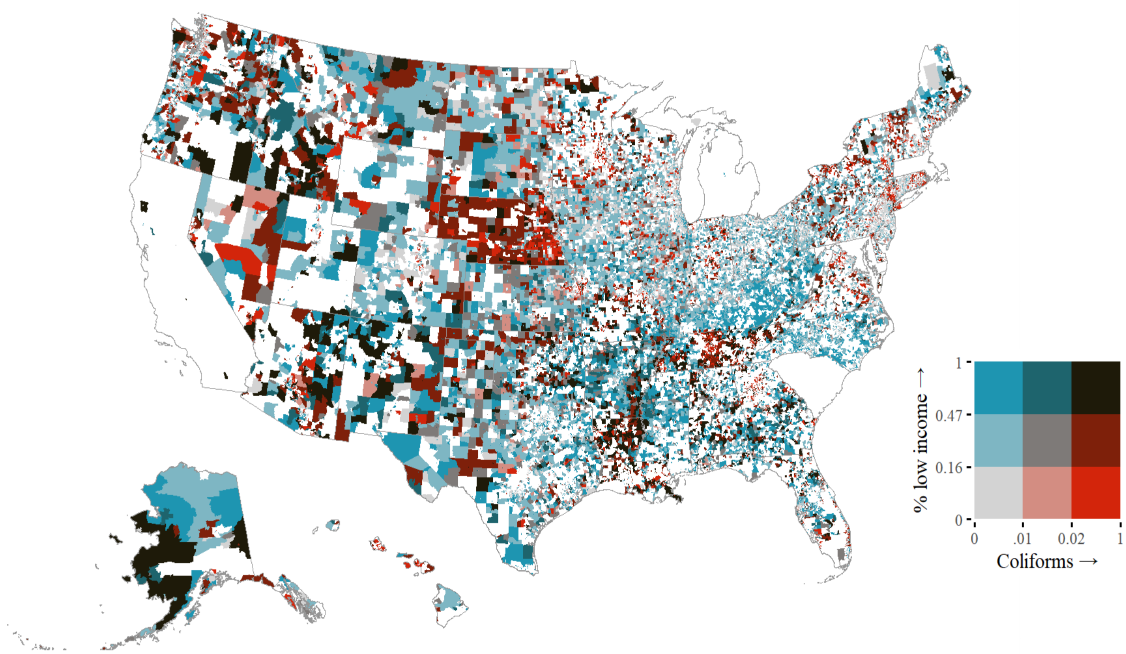
(b) DBP Concentrations and % people living below 2X the Federal Poverty Level

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level. DBP concentrations are the sum of the average total trihalomethane and total haloacetic acid concentrations for each system over the period from 2006-2019.

Figure 12: Bivariate Maps of Total Coliform Detection Share (2006-2019)



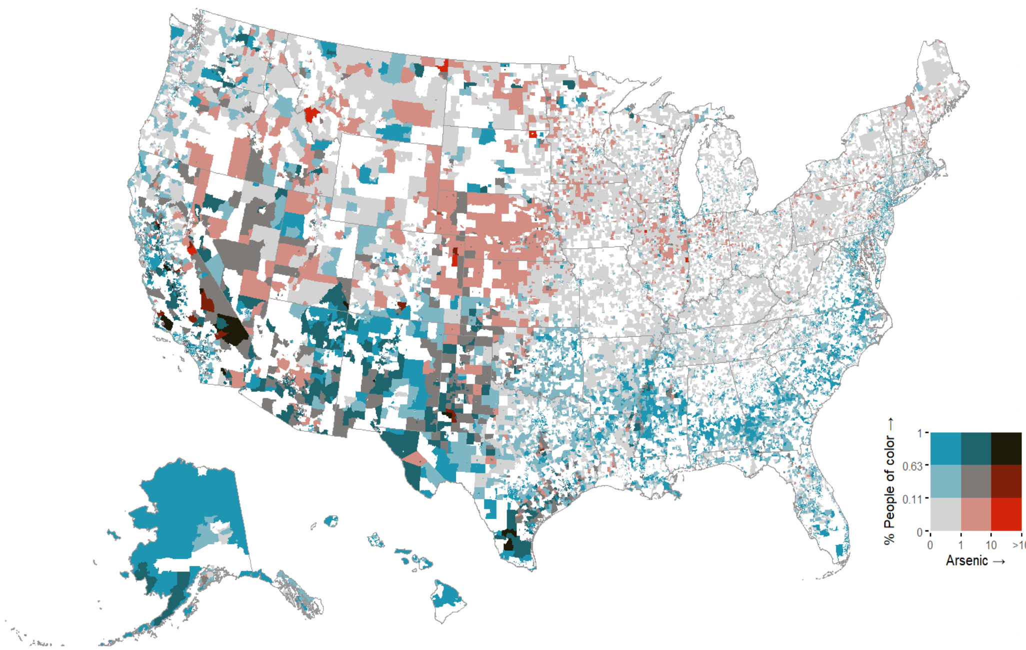
(a) Total Coliform Detection Share and % People of Color



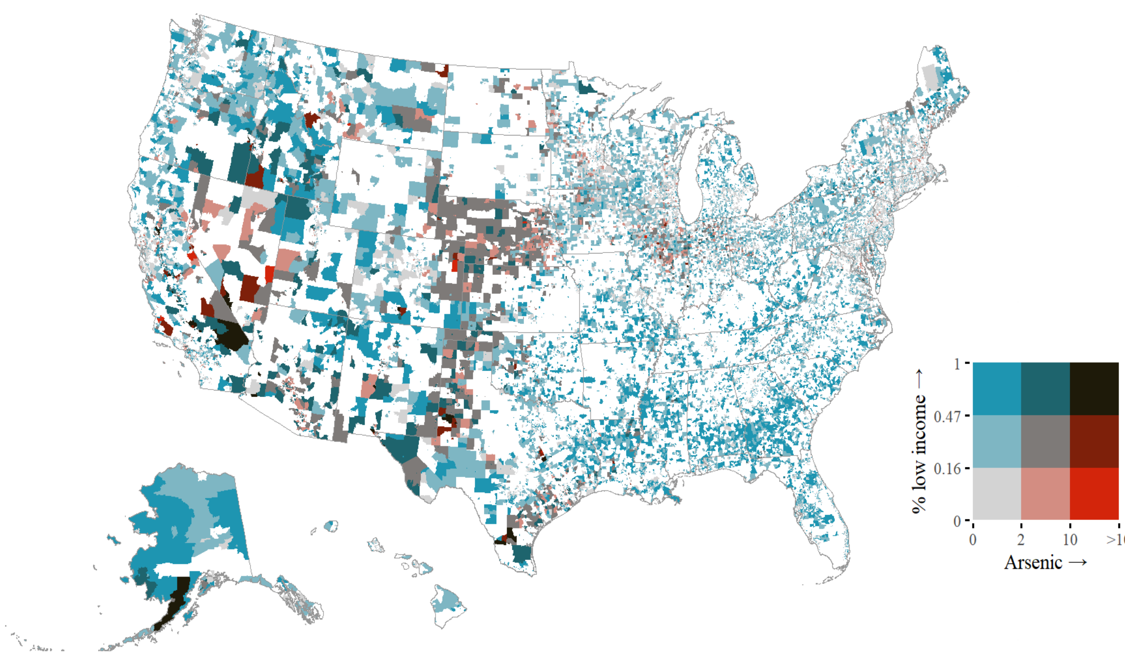
(b) Total Coliform Detection Share and % people living below 2X the Federal Poverty Level

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level. DBP concentrations are the sum of the average total trihalomethane and total haloacetic acid concentrations for each system over the period from 2006-2019.

Figure 13: Bivariate Maps of Arsenic Concentrations in $\mu g/l$ (2006-2019)



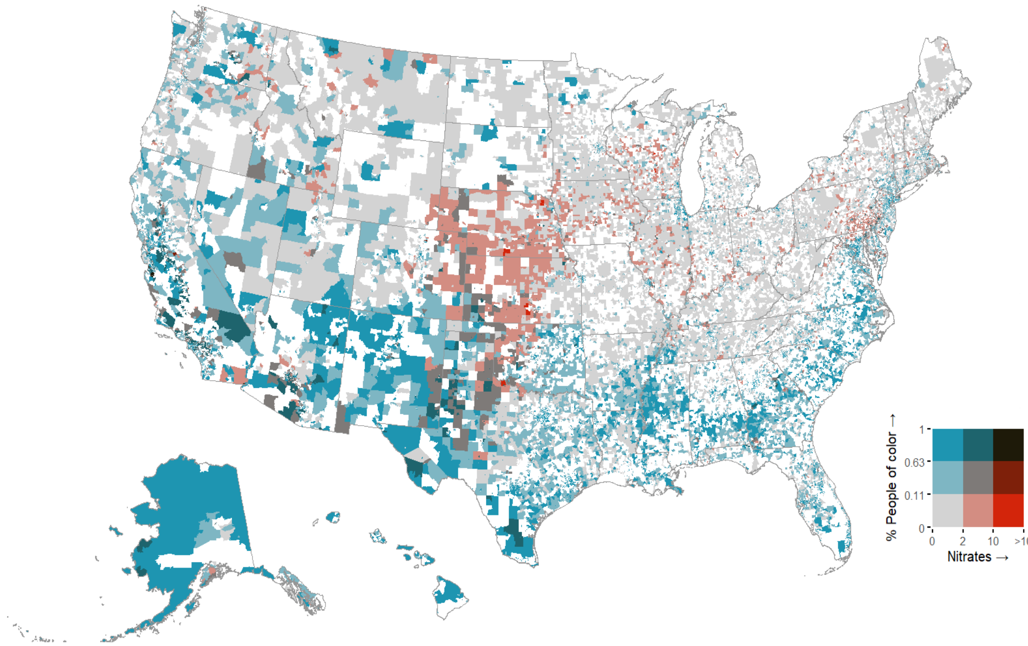
(a) Arsenic Concentration and % People of Color



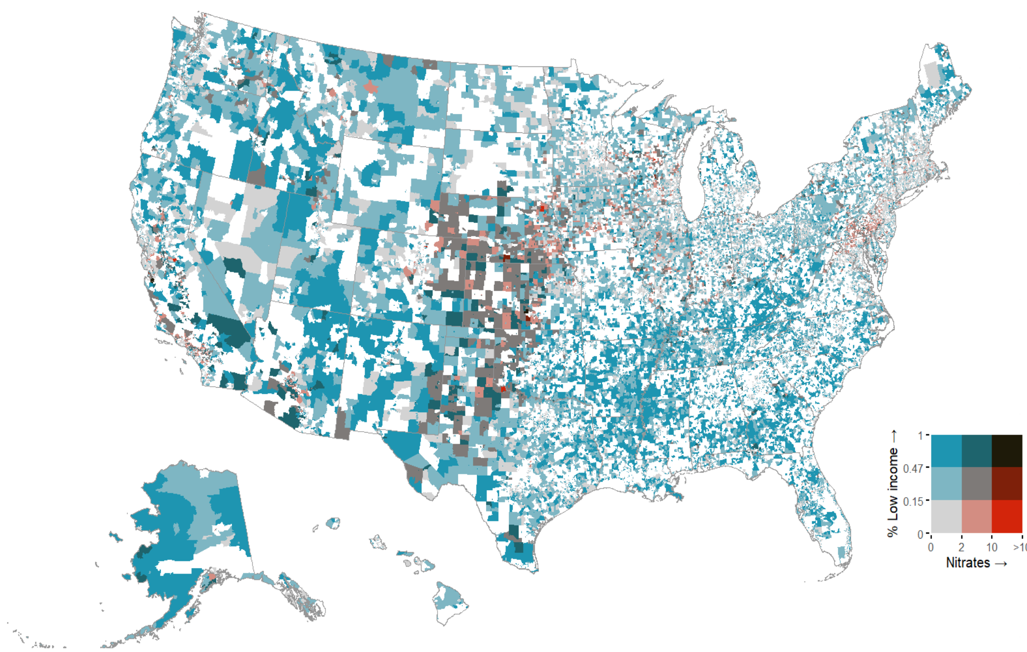
(b) Arsenic Concentration and % people living below 2X the Federal Poverty Level

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level.

Figure 14: Bivariate Maps of Nitrate Concentrations mg/l (2006-2019)



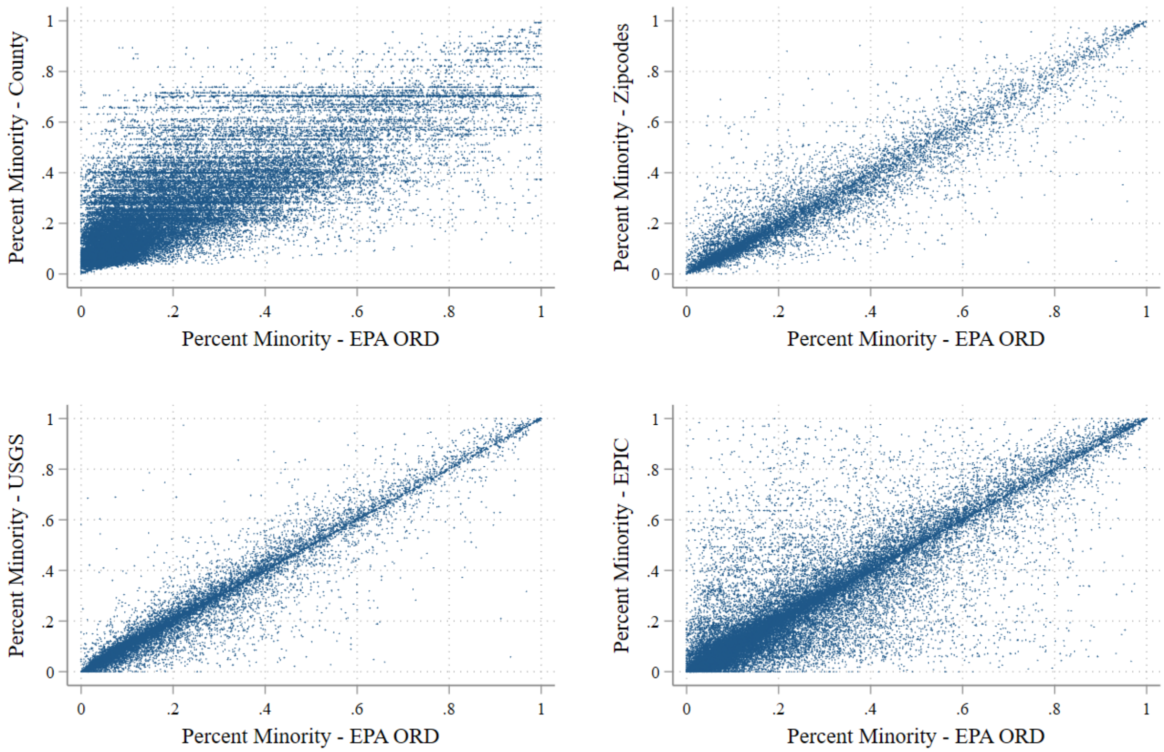
(a) Nitrate Concentrations and % People of Color



(b) Nitrate Concentrations and % people living below 2X the Federal Poverty Level

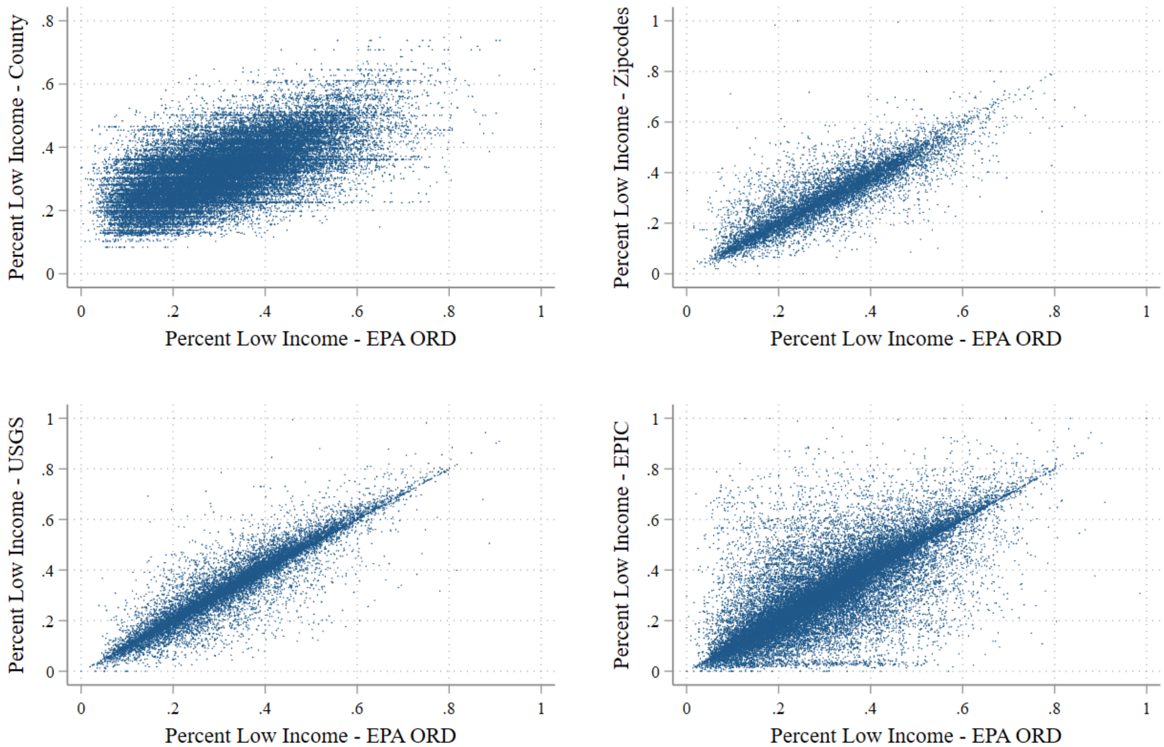
Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level.

Figure 15: Comparing Estimated Percent Minority across Service Area Boundaries



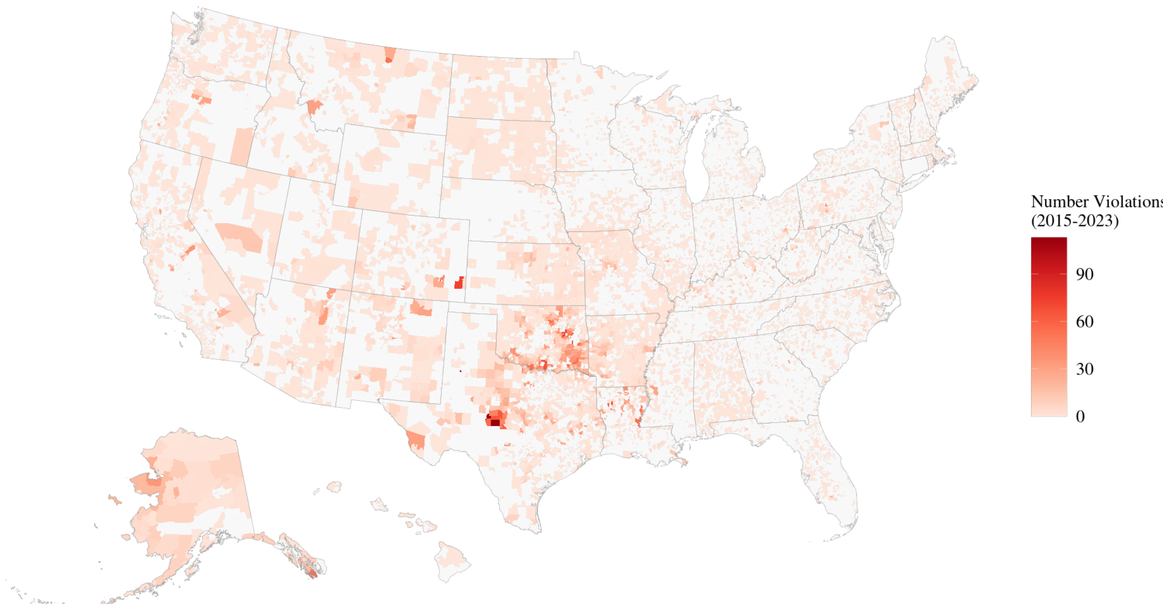
Notes: Scatter plots show the estimated percent of each drinking water system's population that is minority (i.e., Hispanic and/or non-White). The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure 16: Comparing Estimated Percent Low-Income across Service Area Boundaries

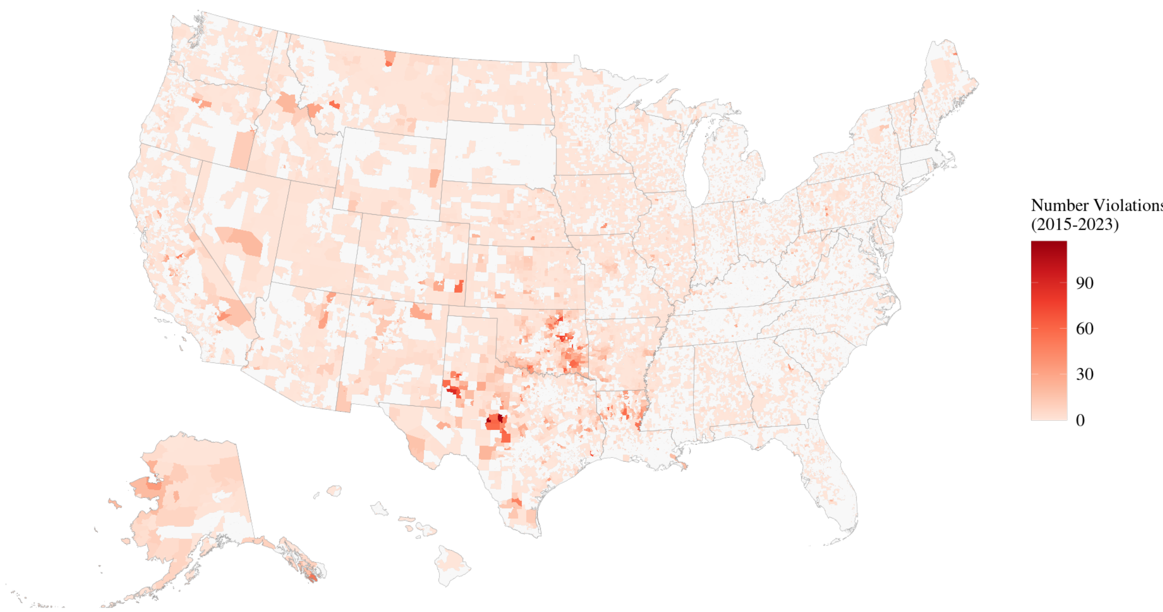


Notes: Scatter plots show estimated percent of each drinking water system's population that is low-income (i.e., income less than twice the Federal Poverty Limit). The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure 17: Geospatial Variation in Service Area Boundary Completeness: Illustrations of Health-Based Violations



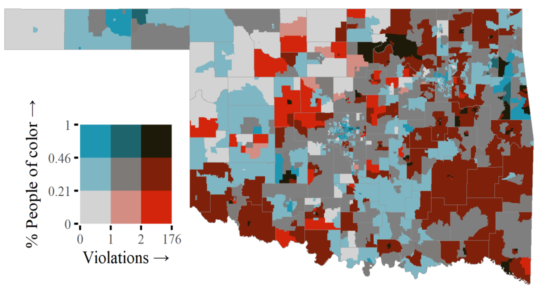
(a) Missing systems in USGS boundaries (90,734 CBGs)



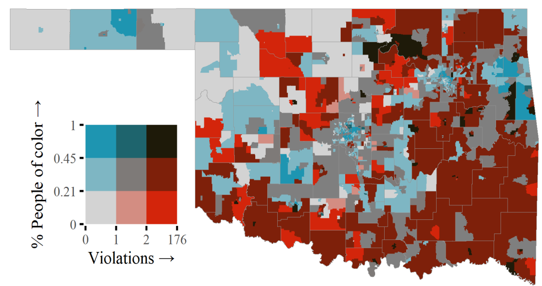
(b) Missing systems in Zip code boundaries (72,083 CBGs)

Notes: Maps display the count of health-based violations of the Safe Drinking Water Act among systems that do not have a geospatial representation in the USGS boundaries or the zip code served information. The figure illustrates that systems without USGS or zip code boundaries display clustering in the South-Central and Western US.

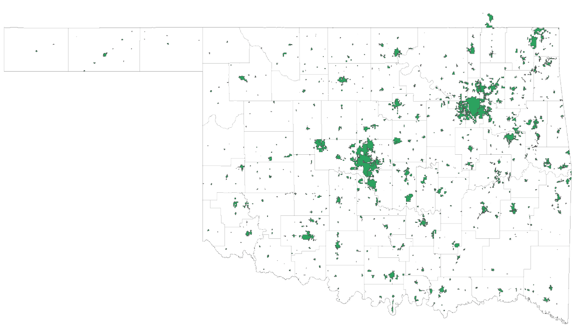
Figure 18: Health-Based Violations in Oklahoma: Visual Comparison of Modelled Boundaries



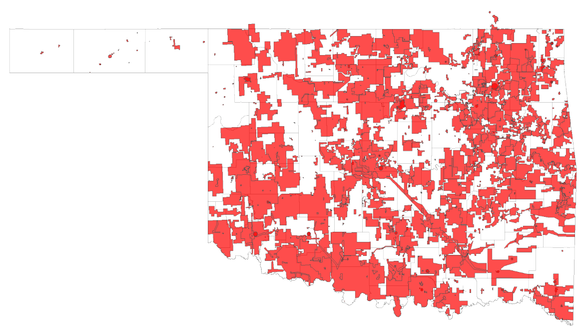
(a) Health-Based Violations and % People of Color using ORD boundaries



(b) Health-Based Violations and % People of Color using EPIC boundaries



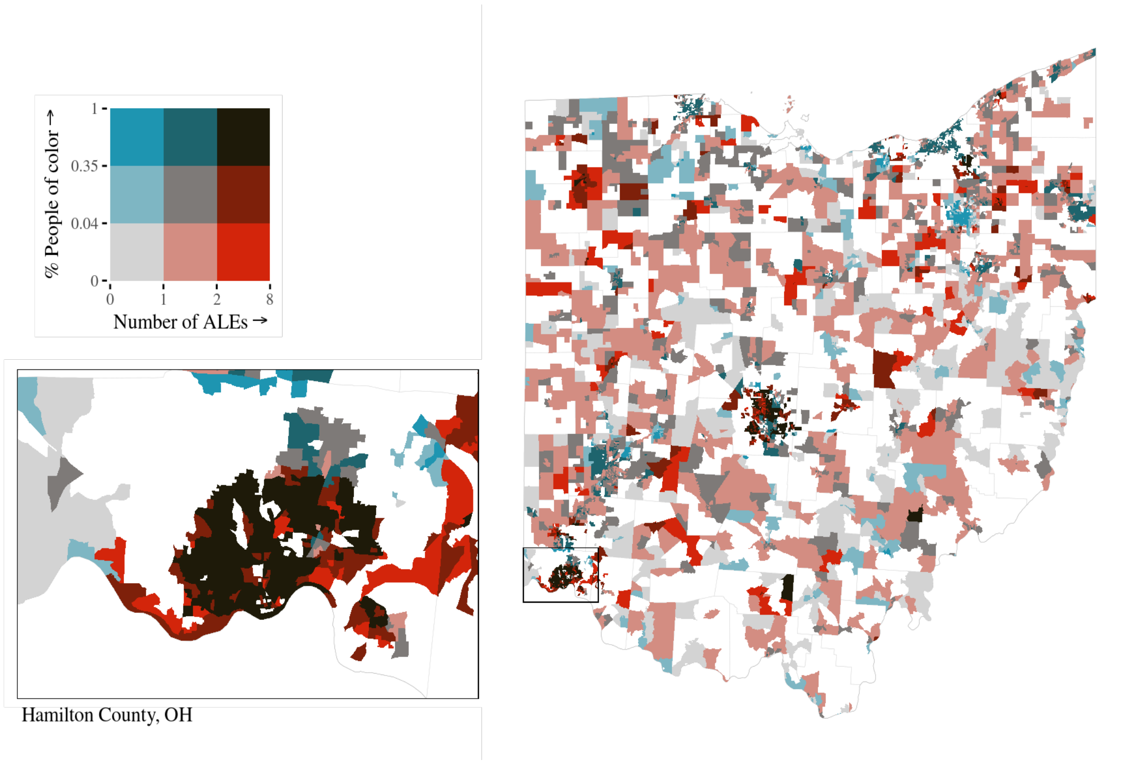
(c) Oklahoma PWS boundaries using ORD boundaries (n = 745)



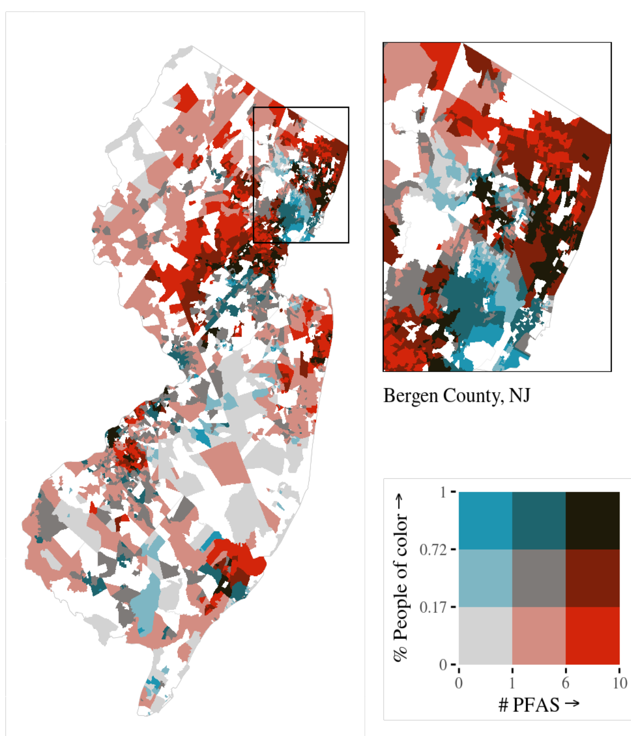
(d) Outline of Oklahoma PWS boundaries using EPIC boundaries (n = 899)

Notes: Demographic information is based on 2021 ACS 5-year data at the census block group level.

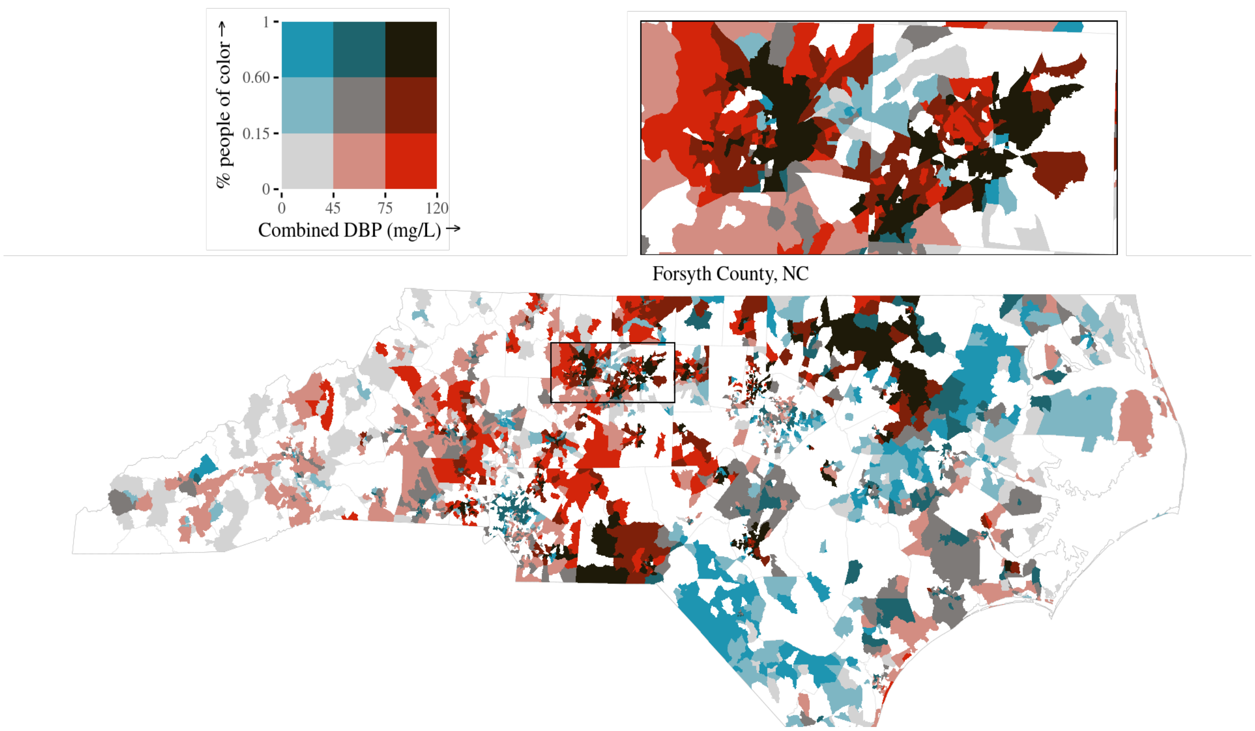
Figure 19: State bivariate maps for selected indicators



(a) Number of Lead Action Level Exceedances (ALEs) between 1991-2020, Ohio



(b) Count of unique PFAS detected in a PWSID between 2013-2023, New Jersey



(c) Disinfection Byproduct (DBP) concentration sums between 2006-2019, North Carolina

Notes: Maps generated using ACS TIGER boundaries based on EPIC Hydroshare version 3.0 boundaries areally apportioned over Census block groups. Each map demonstrates different indicator combinations and locations to show variation within and across states for water quality and EJ indicators.

Tables

Table 1: Summary Statistics of Drinking Water Quality Measures

Boundary	Mean	Median	Max	CWS	% Zero	Total pop
Health-based Violations (2015-2022)						
County	1.352	0.00	366.0	45,934	0.77	310M
Zip Code	0.811	0.00	366.0	16,470	0.83	280M
USGS	1.575	0.00	366.0	18,804	0.74	270M
EPIC	1.354	0.00	366.0	45,492	0.77	310M
EPA ORD	1.349	0.00	366.0	44,331	0.77	310M
Lead Action Level Exceedences (1991-2021)						
County	0.453	0.00	40.0	45,934	0.78	310M
Zip Code	0.438	0.00	40.0	16,470	0.83	280M
USGS	0.447	0.00	34.0	18,804	0.78	270M
EPIC	0.455	0.00	40.0	45,492	0.78	310M
EPA ORD	0.456	0.00	40.0	44,331	0.78	310M
PFAS Concentration (2013-2023)						
County	5.042	0.00	1,020.5	10,956	0.70	270M
Zip Code	6.269	0.00	1,020.5	8,436	0.65	270M
USGS	5.666	0.00	1,020.5	6,013	0.69	230M
EPIC	5.017	0.00	1,020.5	10,932	0.71	270M
EPA ORD	5.054	0.00	1,020.5	10,970	0.70	280M
TTHM & HAA5 Concentrations (2006-2019)						
County	29.988	12.150	661.9	30,460	0.19	290M
Zip Code	41.131	37.985	314.5	9,118	0.07	270M
USGS	28.759	12.300	585.2	13,413	0.17	250M
EPIC	29.947	12.100	661.9	30,448	0.19	280M
EPA ORD	29.867	12.155	661.9	29,515	0.19	290M
Total Coliform Detection Share (2006-2019)						
County	0.019	0.006	0.5	39,589	0.30	240M
Zip Code	0.020	0.003	0.5	8,987	0.21	220M
USGS	0.019	0.006	0.5	16,243	0.26	200M
EPIC	0.019	0.006	0.5	39,508	0.30	240M
EPA ORD	0.019	0.006	0.5	38,052	0.30	240M
Arsenic Concentration (2006-2019)						
County	0.667	0.00	246.7	38,209	0.60	270M
Zip Code	0.562	0.00	73.8	9,011	0.59	250M
USGS	0.701	0.00	62.5	18,316	0.57	260M
EPIC	0.670	0.00	246.7	38,128	0.60	270M
EPA ORD	0.678	0.00	246.7	37,125	0.60	270M
Nitrate Concentration (2006-2019)						
County	0.869	0.167	300.1	39,035	0.20	280M
Zip Code	0.816	0.224	15.5	10,684	0.16	250M
USGS	0.945	0.203	60.9	18,328	0.17	260M
EPIC	0.868	0.167	300.1	38,943	0.20	270M
EPA ORD	0.870	0.167	300.1	37,979	0.20	280M

Table displays the average, median, and maximum values for each drinking water quality indicator across all service area boundary representations. Means are reported at the system level without population weighting. Observation counts differ due to underlying drinking water quality data availability across and varying completeness in the service area boundaries.

Table 2: Average Population-Weighted Drinking Water Quality Measures by Demographic Group

Boundary	American Indian	Asian	Black	Hispanic	Pacific Islander	Non-Hispanic White	POC	Above 2X FPL	Below 2X FPL
Health-based Violations (2015-2022)									
County	2.23	0.59	0.93	0.85	0.44	0.87	0.86	0.83	0.96
Zip Code	2.05	0.53	0.87	0.86	0.36	0.79	0.82	0.76	0.91
USGS	2.47	0.48	0.96	0.81	0.51	0.80	0.83	0.76	0.94
EPIC	2.69	0.51	0.99	0.93	0.35	0.85	0.91	0.81	1.02
EPA ORD	2.76	0.51	0.98	0.93	0.37	0.84	0.91	0.79	1.02
Lead Action Level Exceedences (1991-2021)									
County	0.60	2.01	1.14	0.99	0.82	0.96	1.20	1.09	0.99
Zip Code	0.64	1.76	1.38	1.14	0.80	1.16	1.31	1.23	1.21
USGS	0.70	1.77	1.32	1.15	1.07	1.19	1.30	1.25	1.21
EPIC	0.63	1.67	1.28	1.05	0.77	0.97	1.21	1.07	1.08
EPA ORD	0.59	1.70	1.35	1.06	0.88	1.09	1.24	1.17	1.12
PFAS Concentrations (2013-2023)									
County	7.44	8.57	10.42	16.70	5.54	7.43	12.82	9.49	10.36
Zip Code	6.74	9.45	9.00	13.12	5.90	7.02	10.82	8.55	8.83
USGS	5.68	9.56	9.40	16.15	5.79	7.19	12.18	9.27	9.59
EPIC	7.37	9.56	7.51	14.16	5.54	6.92	10.78	8.72	8.47
EPA ORD	7.32	9.55	8.82	13.24	5.36	6.80	10.82	8.45	8.73
TTHM & HAA5 Concentrations (2006-2019)									
County	44.57	47.32	50.07	43.92	31.72	46.45	46.41	46.36	46.59
Zip Code	44.64	45.17	51.74	43.98	32.36	47.59	46.66	47.00	47.64
USGS	45.68	47.35	52.69	45.35	42.18	46.00	48.18	46.65	47.63
EPIC	43.38	45.55	50.17	43.46	30.47	46.51	46.04	46.10	46.74
EPA ORD	41.43	45.06	51.10	43.58	32.13	46.06	46.22	45.91	46.60
Total Coliform Detection Share (2006-2019)									
County	0.03	0.08	0.06	0.04	0.10	0.04	0.05	0.04	0.04
Zip Code	0.03	0.07	0.06	0.04	0.10	0.04	0.05	0.05	0.05
USGS	0.03	0.06	0.06	0.04	0.05	0.04	0.05	0.04	0.05
EPIC	0.03	0.07	0.06	0.04	0.11	0.04	0.05	0.04	0.05
EPA ORD	0.03	0.07	0.06	0.04	0.10	0.04	0.05	0.04	0.04
Arsenic Concentration (2006-2019)									
County	0.67	0.46	0.28	0.75	0.58	0.40	0.54	0.45	0.49
Zip Code	0.88	0.47	0.27	0.73	0.59	0.38	0.53	0.43	0.48
USGS	0.80	0.37	0.19	0.59	0.67	0.35	0.42	0.37	0.40
EPIC	0.84	0.49	0.26	0.74	0.54	0.41	0.53	0.45	0.48
EPA ORD	0.97	0.47	0.27	0.75	0.57	0.40	0.55	0.45	0.49
Nitrate Concentration (2006-2019)									
County	0.77	1.13	0.61	1.11	1.05	0.77	0.95	0.85	0.84
Zip Code	0.76	1.25	0.60	1.15	1.08	0.76	0.97	0.85	0.84
USGS	0.69	0.91	0.56	0.87	0.91	0.69	0.76	0.73	0.71
EPIC	0.78	1.23	0.58	1.14	1.09	0.77	0.95	0.86	0.83
EPA ORD	0.74	1.22	0.59	1.15	1.06	0.76	0.96	0.85	0.84

Table displays the average value for each drinking water quality indicator across all service area boundary representations. Note that the observation count can differ due to differential underlying drinking water quality data across indicators as well as due to varying levels of completeness with respect to the service area boundaries.

Table 3: Disparity Measures by Service Area Type

	County	Zip code	USGS	EPIC	EPA ORD
Health-based Violations (2015-2022)					
American Indian	2.56	2.60	3.08	3.16	3.29
Asian	0.68	0.67	0.60	0.60	0.61
Black	1.07	1.10	1.20	1.16	1.17
Hispanic	0.97	1.09	1.01	1.10	1.11
Pacific Islander	0.50	0.45	0.64	0.41	0.45
Low Income	1.16	1.19	1.24	1.27	1.29
Lead Action Level Exceedences (1991-2021)					
American Indian	0.62	0.56	0.59	0.66	0.54
Asian	2.09	1.52	1.48	1.73	1.55
Black	1.18	1.19	1.10	1.32	1.24
Hispanic	1.03	0.98	0.96	1.09	0.97
Pacific Islander	0.86	0.69	0.90	0.80	0.81
Low Income	0.91	0.99	0.97	1.01	0.96
PFAS Concentrations (2013-2023)					
American Indian	1.00	0.96	0.79	1.06	1.08
Asian	1.15	1.35	1.33	1.38	1.40
Black	1.40	1.28	1.31	1.08	1.30
Hispanic	2.25	1.87	2.25	2.05	1.95
Pacific Islander	0.74	0.84	0.80	0.80	0.79
Low Income	1.09	1.03	1.03	0.97	1.03
TTHM HAA5 Concentrations (2006-2019)					
American Indian	0.96	0.94	0.99	0.93	0.90
Asian	1.02	0.95	1.03	0.98	0.98
Black	1.08	1.09	1.15	1.08	1.11
Hispanic	0.95	0.92	0.99	0.93	0.95
Pacific Islander	0.68	0.68	0.92	0.66	0.70
Low Income	1.00	1.01	1.02	1.01	1.02
Total Coliform Detection Share (2006-2019)					
American Indian	0.84	0.71	0.77	0.77	0.76
Asian	2.16	1.67	1.54	1.83	1.77
Black	1.49	1.49	1.41	1.61	1.54
Hispanic	1.05	1.05	1.07	1.08	1.08
Pacific Islander	2.64	2.41	1.15	2.88	2.50
Low Income	0.98	1.03	1.05	1.06	1.04
Arsenic Concentration (2006-2019)					
American Indian	1.67	2.30	2.32	2.04	2.43
Asian	1.15	1.23	1.06	1.18	1.18
Black	0.70	0.69	0.56	0.63	0.67
Hispanic	1.86	1.90	1.72	1.80	1.87
Pacific Islander	1.45	1.55	1.94	1.30	1.43
Low Income	1.10	1.11	1.09	1.06	1.11
Nitrate Concentration (2006-2019)					
American Indian	0.99	1.00	0.99	1.01	0.97
Asian	1.47	1.64	1.31	1.59	1.61
Black	0.79	0.79	0.80	0.75	0.77
Hispanic	1.44	1.52	1.26	1.47	1.51
Pacific Islander	1.36	1.42	1.31	1.40	1.40
Low Income	1.00	0.99	0.98	0.97	0.99

Table displays the disparity metrics across the two groups listed in each row. TTHM & HAA5 Concentrations and Total Coliform Detection Share represent system-level average calculations for each chemical over the period 2006-2019, which are summed across TTHM and HAA5 to derive a total DBP concentration.

Table 4: Demographic Regression Results according to EPA ORD Service Area Boundaries

	(1) Health Violations	(2) Lead ALEs	(3) PFAS Conc.	(4) DBP Conc.	(5) Coliform Detection	(6) Arsenic Conc.	(7) Nitrate Conc.
% American Indian	5.368***	0.093	2.768	−1.824	0.012***	0.970***	−0.231
	(0.401)	(0.092)	(6.104)	(2.449)	(0.003)	(0.166)	(0.200)
% Asian	−4.786***	0.814***	16.055***	−42.699***	0.007	0.836***	1.940***
	(0.695)	(0.159)	(4.850)	(4.281)	(0.006)	(0.303)	(0.354)
% Black	−0.431*	−0.046	5.746***	0.864	−0.002	−0.785***	−1.163***
	(0.230)	(0.053)	(1.913)	(1.303)	(0.002)	(0.097)	(0.116)
% Hispanic	2.610***	−0.286***	8.271***	−15.243***	−0.014***	1.736***	1.554***
	(0.184)	(0.042)	(1.627)	(1.162)	(0.001)	(0.076)	(0.091)
% Pacific Islander	−1.794	0.173	−87.538**	−7.926	0.122***	−0.771	−0.216
	(2.642)	(0.606)	(43.002)	(14.335)	(0.017)	(1.088)	(1.314)
% Low income+	2.154***	−0.325***	−8.353***	21.006***	0.007***	−0.190**	−0.111
	(0.213)	(0.049)	(1.905)	(1.339)	(0.001)	(0.091)	(0.108)
Tribal System	−2.157***	−0.009	−2.292	−10.333***	0.005**	0.356***	−0.122
	(0.317)	(0.073)	(4.300)	(1.957)	(0.002)	(0.132)	(0.159)
Very Large system	−1.387***	0.481***	2.333*	−2.813*	0.044***	−0.088	0.119
	(0.297)	(0.068)	(1.341)	(1.558)	(0.002)	(0.123)	(0.146)
Large system++	−0.663***	0.198***	−0.707	−1.132	0.014***	−0.090	0.067
	(0.128)	(0.029)	(0.661)	(0.690)	(0.001)	(0.056)	(0.066)
Small system	0.319***	−0.026	−2.158***	−0.356	0.0001	0.038	0.128**
	(0.101)	(0.023)	(0.786)	(0.556)	(0.001)	(0.044)	(0.053)
Very small system	0.367***	−0.046**	−0.708	−6.309***	0.009***	0.137***	0.255***
	(0.098)	(0.022)	(0.764)	(0.563)	(0.001)	(0.042)	(0.050)
Groundwater	−1.579***	−0.197***	−0.907	−45.328***	0.004***	0.324***	0.074*
	(0.073)	(0.017)	(0.564)	(0.407)	(0.001)	(0.037)	(0.043)
Constant	1.440***	0.734***	7.111***	58.787***	0.008***	0.212***	0.539***
	(0.114)	(0.026)	(0.824)	(0.657)	(0.001)	(0.053)	(0.062)
Observations	44,287	44,287	10,970	29,515	38,052	37,125	37,979

Notes: *p<0.1; **p<0.05; ***p<0.01. % Low income refers to the % of the population served with incomes below twice the Federal Poverty Level. System size categories are based on the population served by the system, where medium-sized systems are the omitted category. Very small systems serve fewer than 500 individuals, small systems serve 501-3,300, large systems serve 10,000 to 100,000, and very large systems serve over 100,000 people.

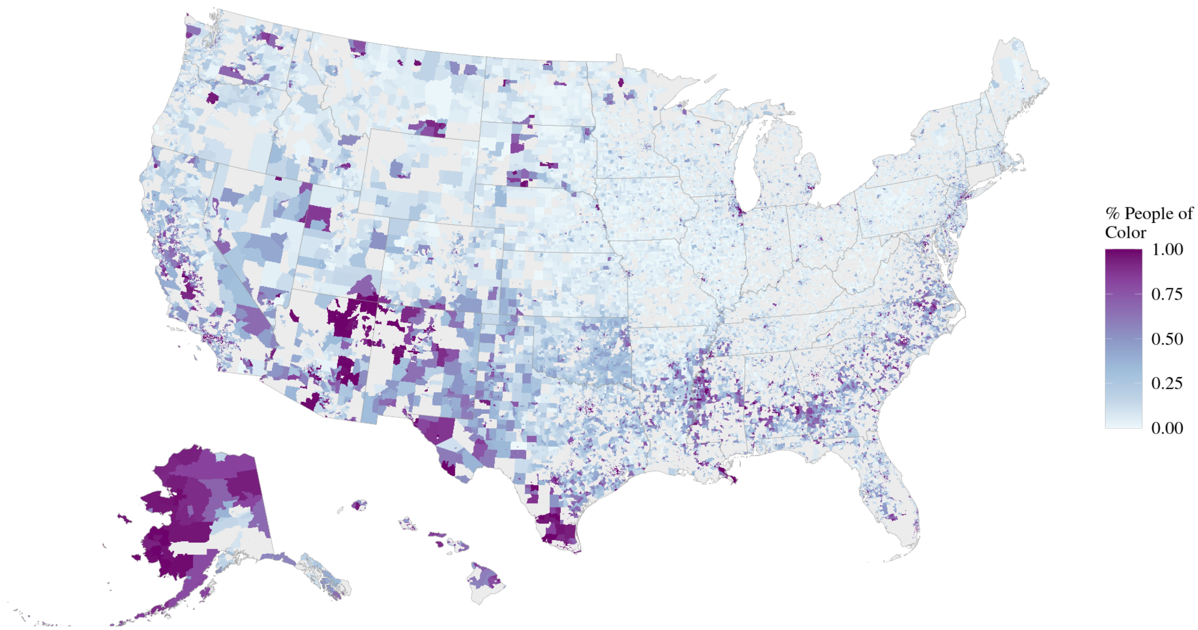
Table 5: Drinking Water Quality Concerns Co-Occur with Other Environmental Burdens

	(1) Health Violations	(2) Lead ALEs	(3) PFAS Conc.	(4) DBP Conc.	(5) Coliform Detection	(6) Arsenic Conc.	(7) Nitrate Conc.
Lead Paint	0.400***	1.277***	−2.755**	17.581***	−0.0001	0.085	1.033***
	(0.025)	(0.040)	(1.284)	(1.308)	(0.001)	(0.053)	(0.097)
Ozone	0.022***	−0.002	−0.058	−0.189***	−0.0001***	0.035***	0.050***
	(0.001)	(0.001)	(0.043)	(0.044)	(0.00004)	(0.002)	(0.003)
$PM_{2.5}$	0.085***	−0.103***	0.020	1.043***	−0.002***	0.032***	0.039***
	(0.003)	(0.005)	(0.157)	(0.172)	(0.0002)	(0.006)	(0.011)
Toxic Release Facility	−0.361***	0.136***	0.478***	1.325***	0.002***	−0.036***	0.102***
	(0.010)	(0.003)	(0.159)	(0.227)	(0.0003)	(0.010)	(0.018)
Wastewater discharge	−0.0002***	−0.0002**	−0.0003	−0.001	−0.00000	−0.00002	0.00004
	(0.0001)	(0.0001)	(0.001)	(0.0004)	(0.00000)	(0.00002)	(0.00003)
Superfund Site	−1.276***	0.197***	7.316***	−7.730***	−0.004***	−0.186***	0.274**
	(0.060)	(0.035)	(1.196)	(1.508)	(0.002)	(0.065)	(0.118)
Constant	−1.214***	−0.333***	6.939***	26.227***	0.041***	−1.098***	−1.871***
	(0.041)	(0.075)	(2.073)	(2.391)	(0.002)	(0.088)	(0.159)
State control	No	No	No	No	No	No	No
Observations	34,189	34,189	9,269	24,086	30,027	28,177	28,946

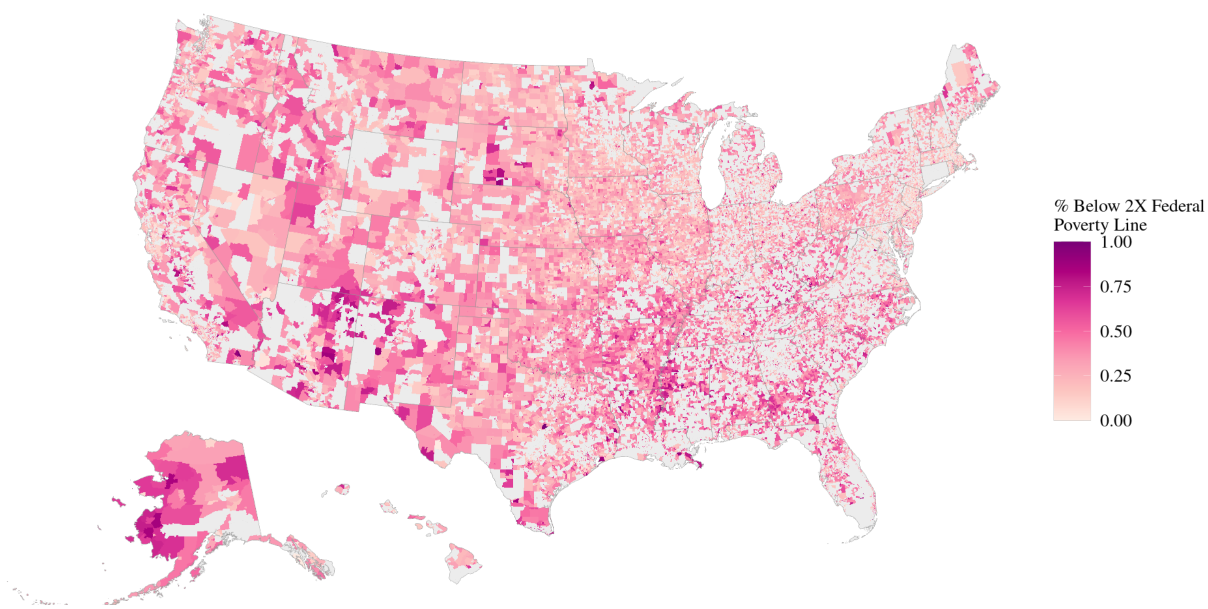
Notes: *p<0.1; **p<0.05; ***p<0.01. Each row represents a specific EJSCREEN environmental indicator. These include potential community-level exposure to lead paint, ozone levels, fine particulate matter, proximity to hazardous waste sites, wastewater discharge, and superfund site proximity.

Appendix

Figure A1: Race and income demographic maps



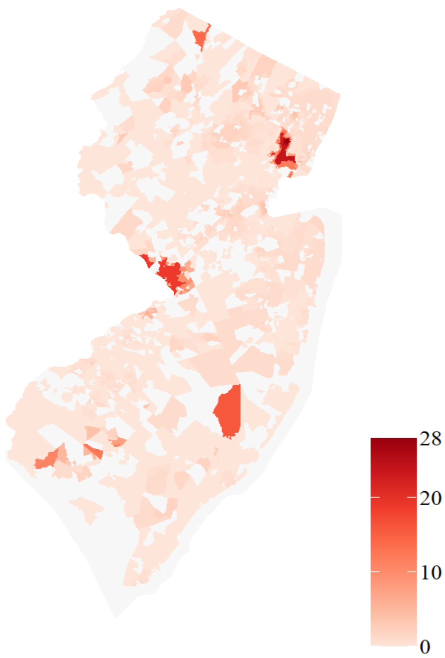
(a) Country-wide showing % People of Color in each Census Block Group



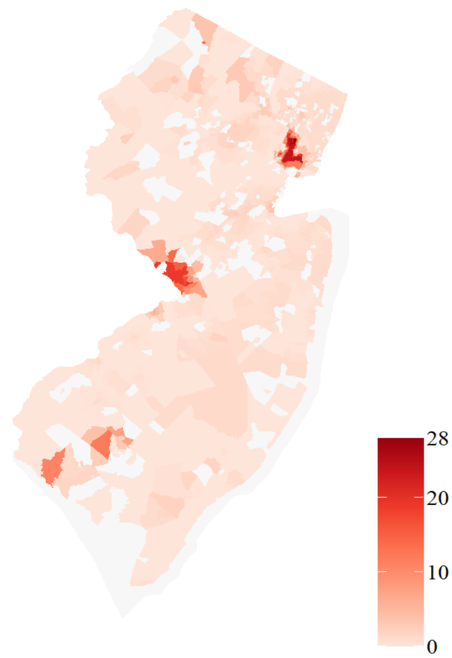
(b) Country-wide showing % people living below 2X the Federal Poverty Level in each Census Block Group

Notes: Demographic indicators based on EJScreen documentation updated with the 2020 US Census data.

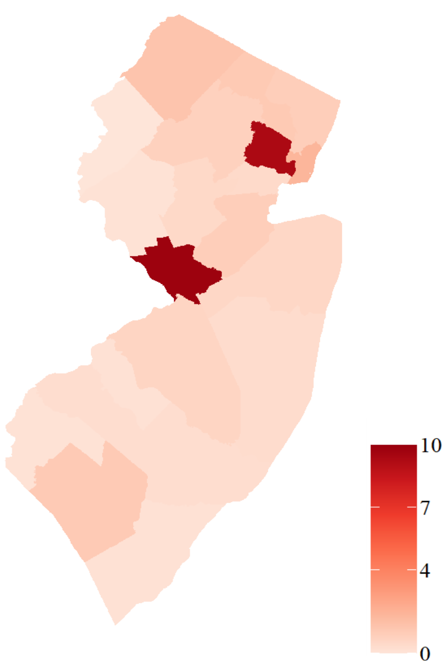
Figure A2: Average number of health-based violations in New Jersey at the CBG, tract, and county level



(a) Census block group level



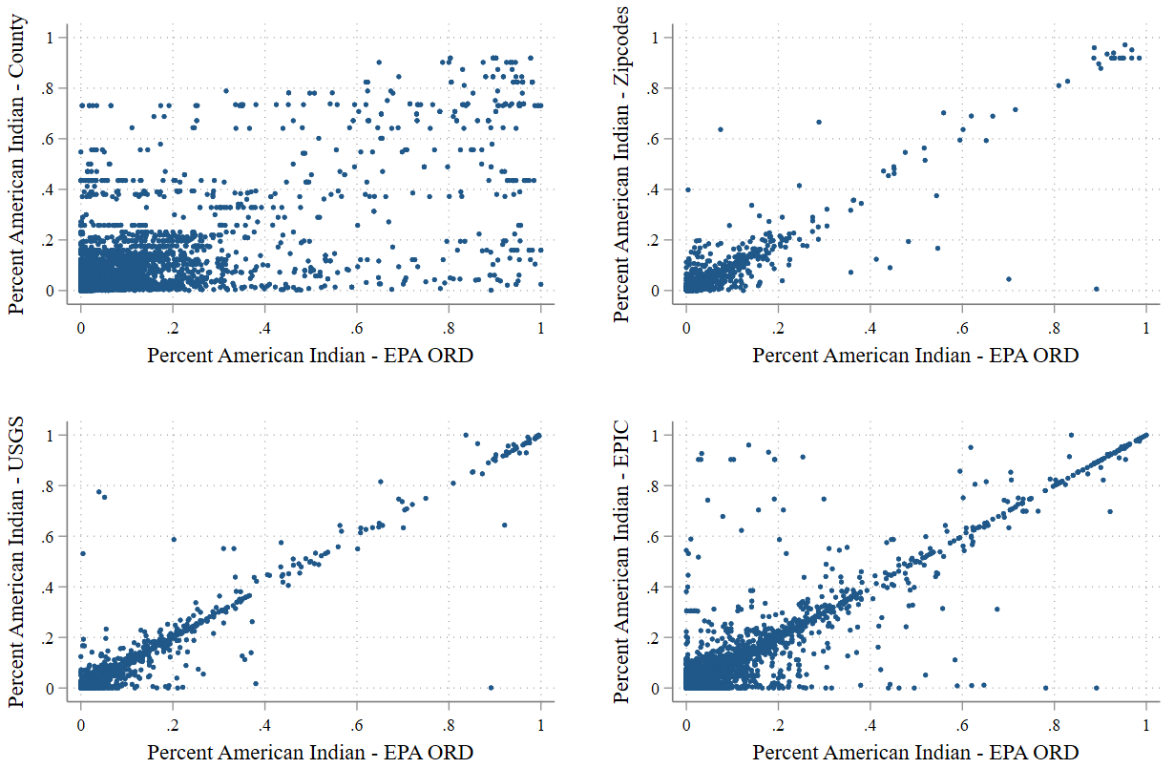
(b) Census tract level



(c) County level

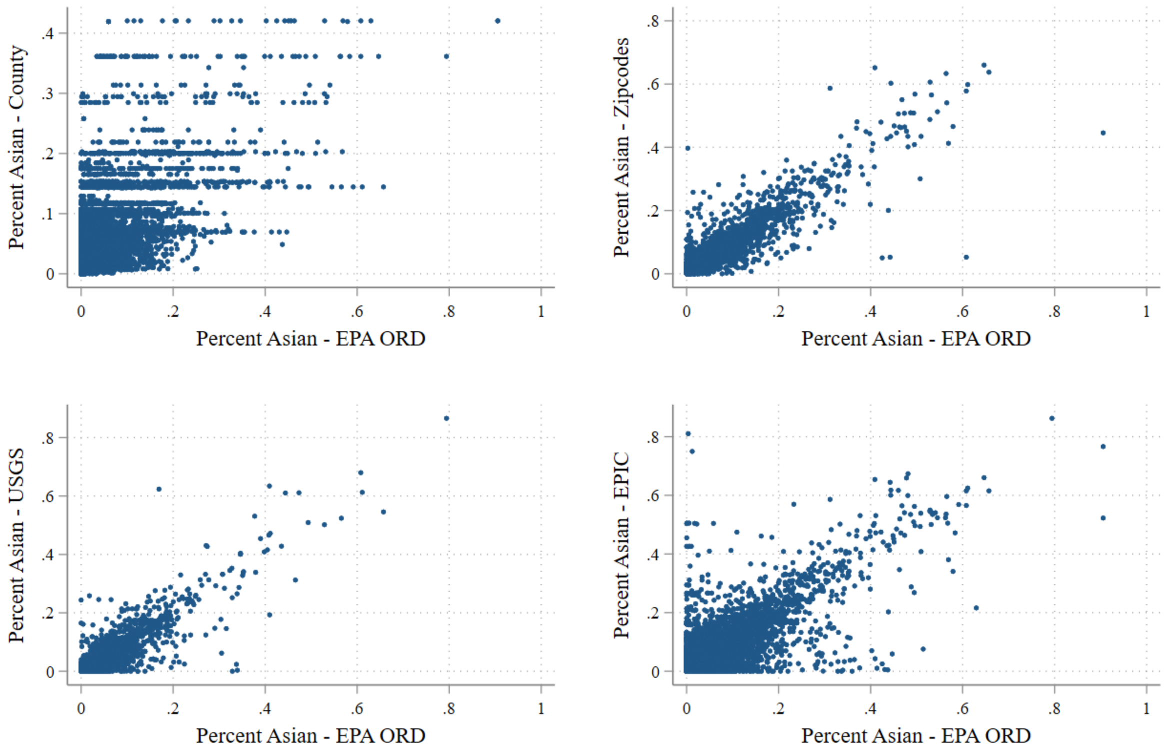
Notes: Maps generated using ORD boundaries aerally interpolated into ACS TIGER boundaries. Each map averages the number of violations per CWS over the spatial boundary. Note that the scales are different as the number of violations represent weighted averages for each boundary type. Gray regions reflect missing drinking water quality data or that the area is not served by public water with known boundaries.

Figure A3: Comparing Estimated Percent American Indian across Service Area Boundaries



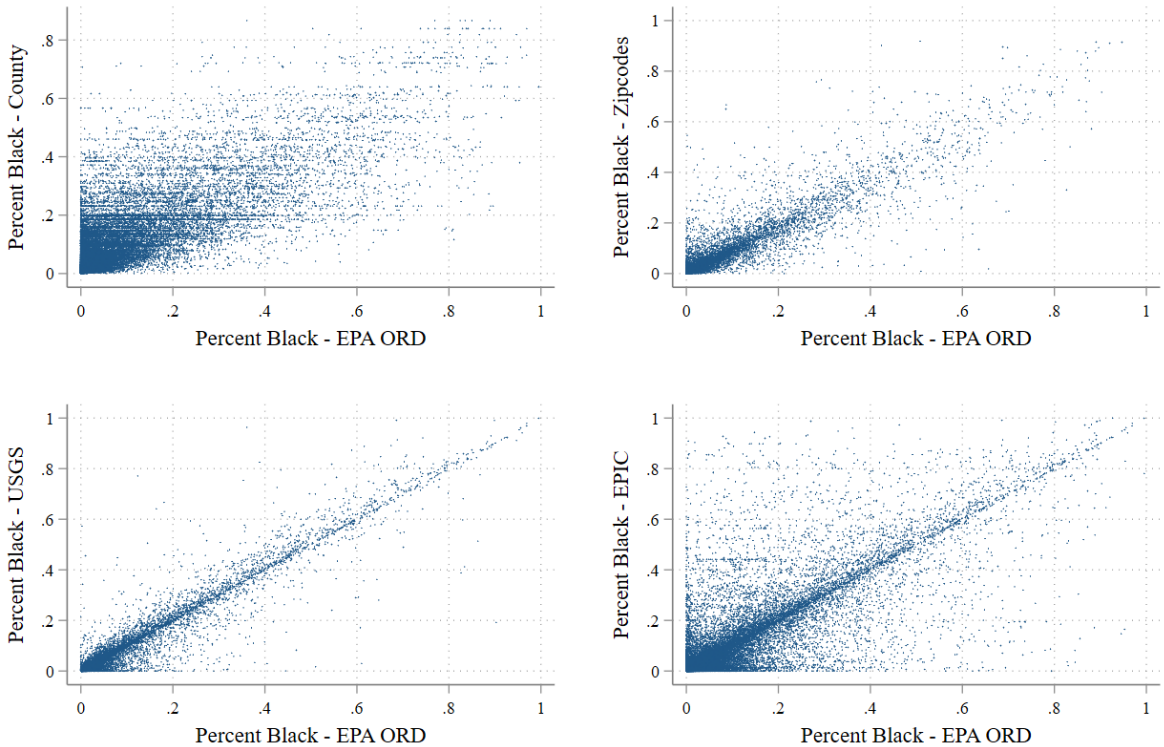
Notes: Scatter plots show estimated percent of each drinking water system's population that is American Indian. The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure A4: Comparing Estimated Percent Asian across Service Area Boundaries



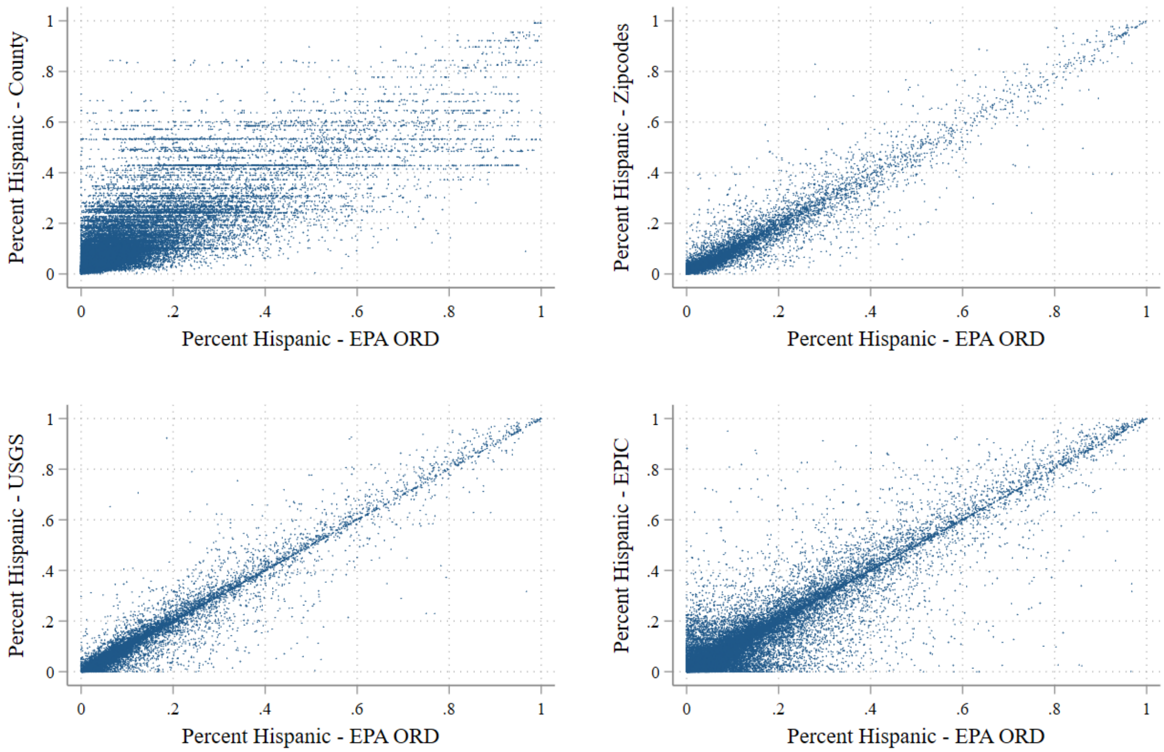
Notes: Scatter plots show estimated percent of each drinking water system's population that is Asian. The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure A5: Comparing Estimated Percent Black across Service Area Boundaries



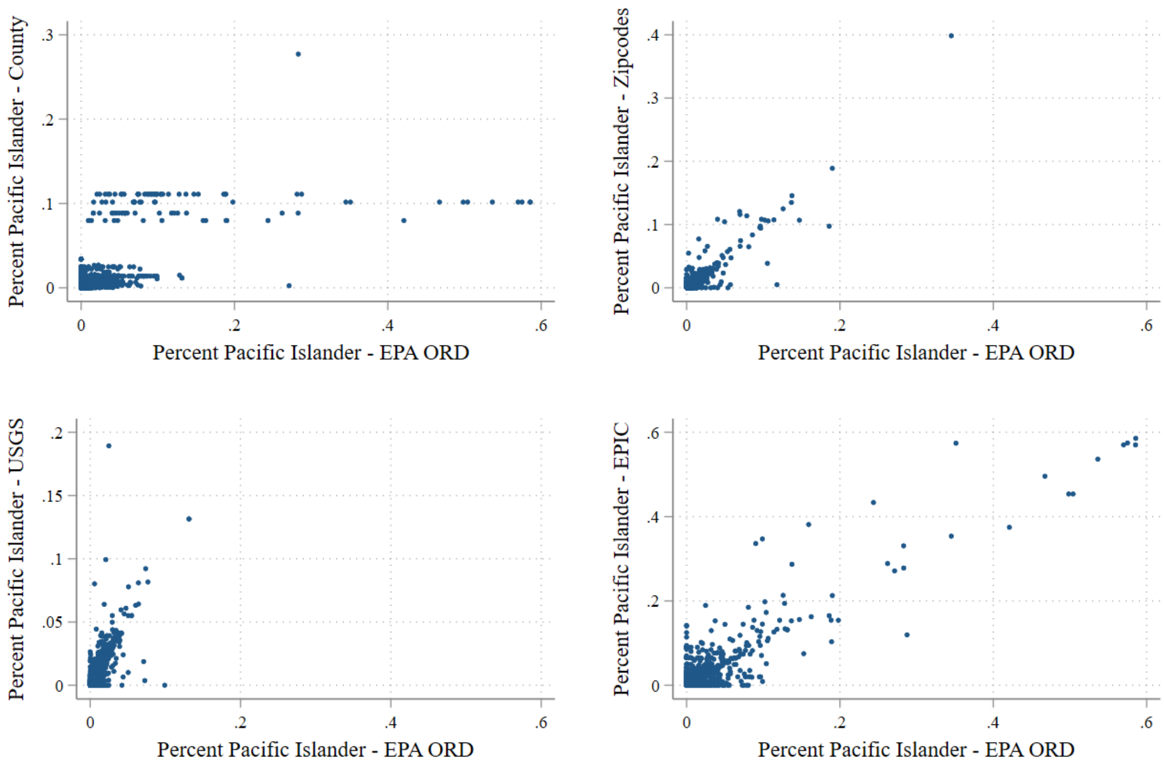
Notes: Scatter plots show estimated percent of each drinking water system's population that is Black. The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure A6: Comparing Estimated Percent Hispanic across Service Area Boundaries



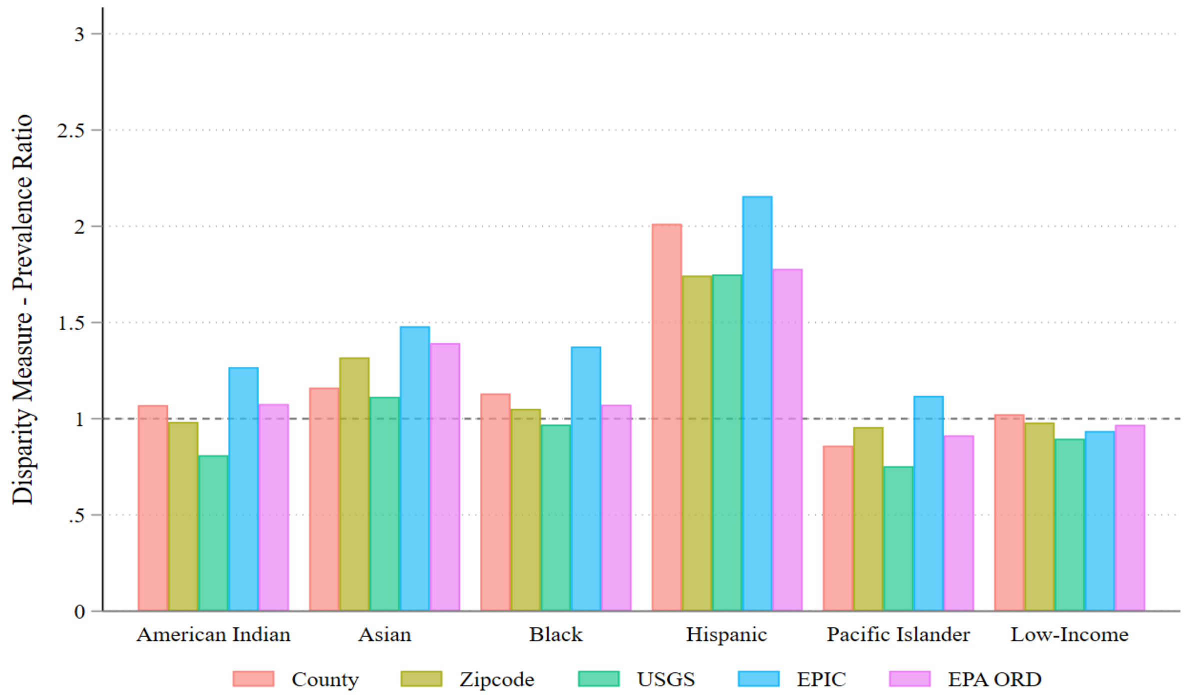
Notes: Scatter plots show estimated percent of each drinking water system's population that is Hispanic. The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure A7: Comparing Estimated Percent Pacific Islander across Service Area Boundaries

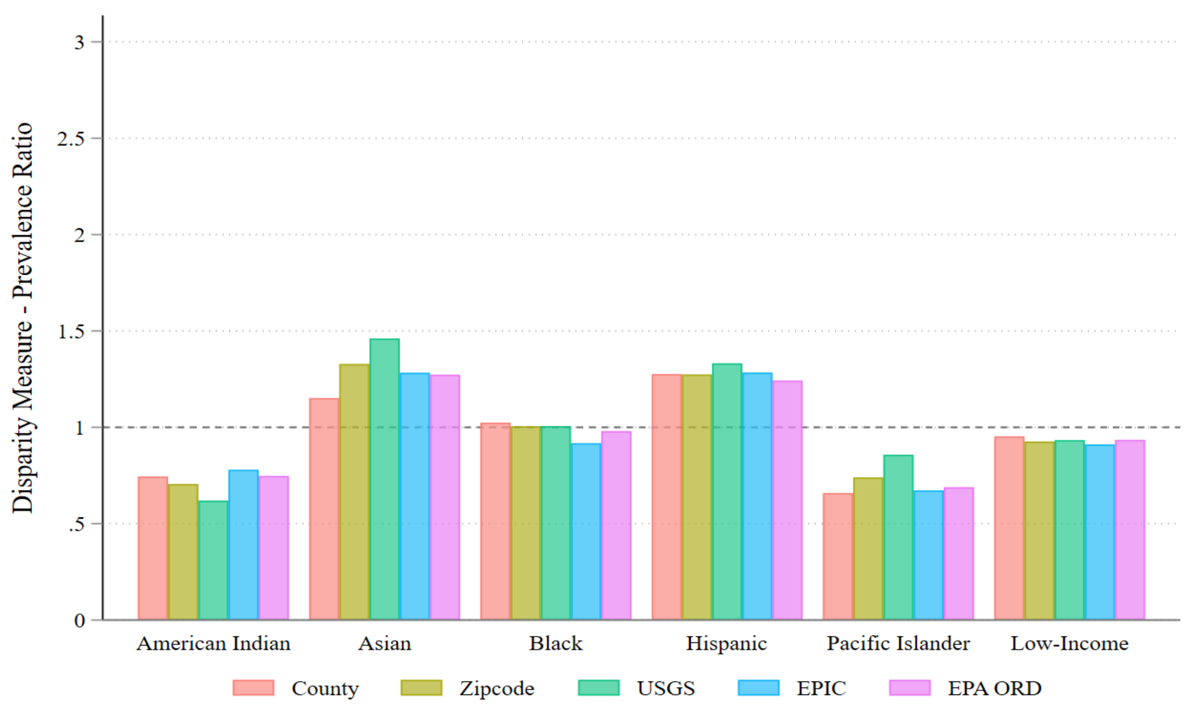


Notes: Scatter plots show estimated percent of each drinking water system's population that is Pacific Islander. The x axis represents the percentage according to EPA ORD boundaries, while the y axis represents the percentage according to county, zip code, USGS, or EPIC boundaries.

Figure A8: Disparity Measures According to Alternative Indicators of PFAS in Drinking Water

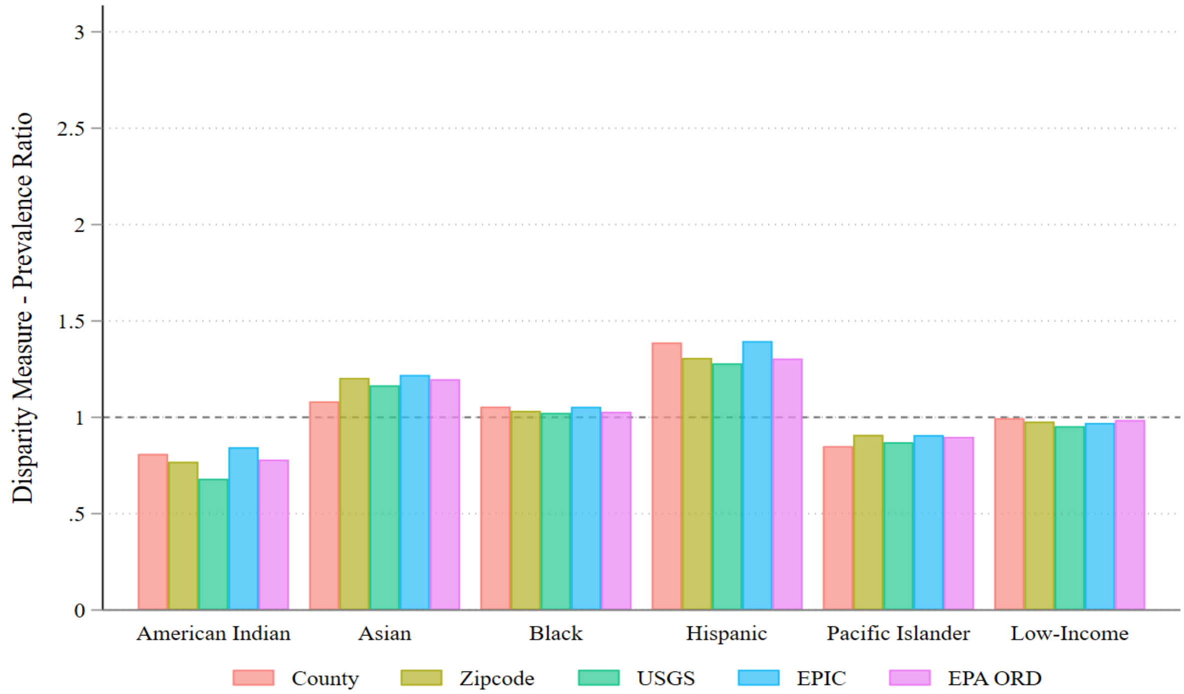


(a) Sum of Maximum PFAS Concentrations

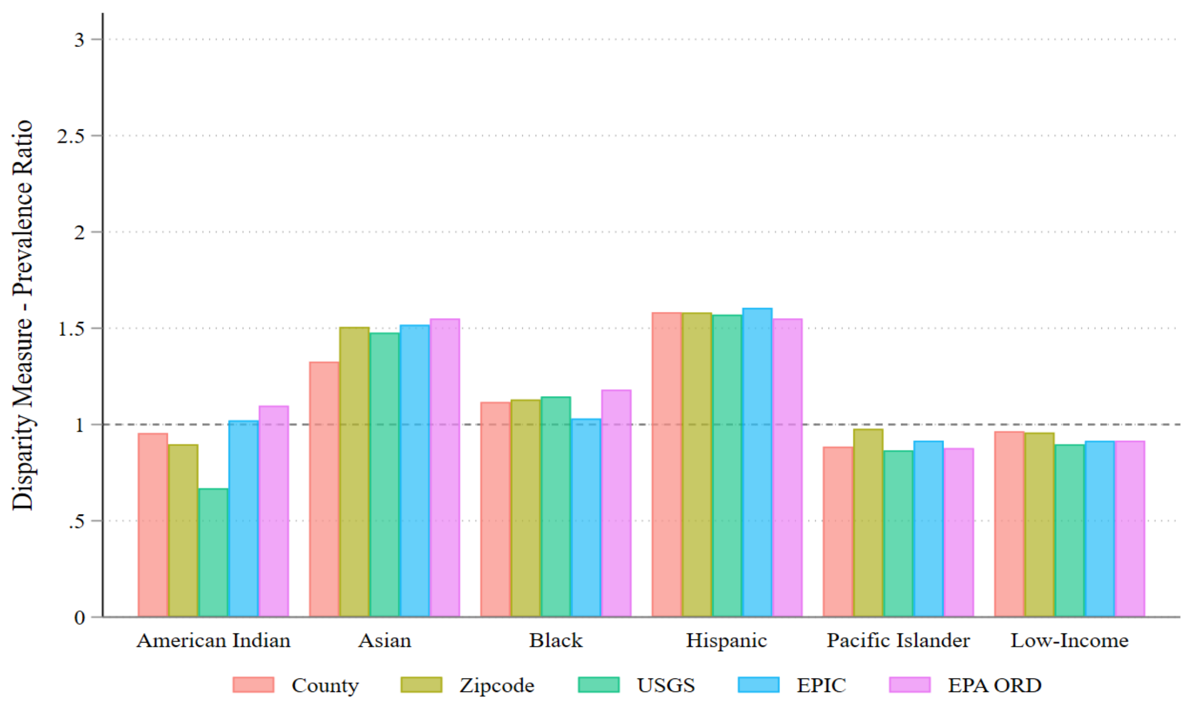


(b) PFAS Detection Share

Figure A8: Disparity Measures According to Alternative Indicators of PFAS in Drinking Water (continued)



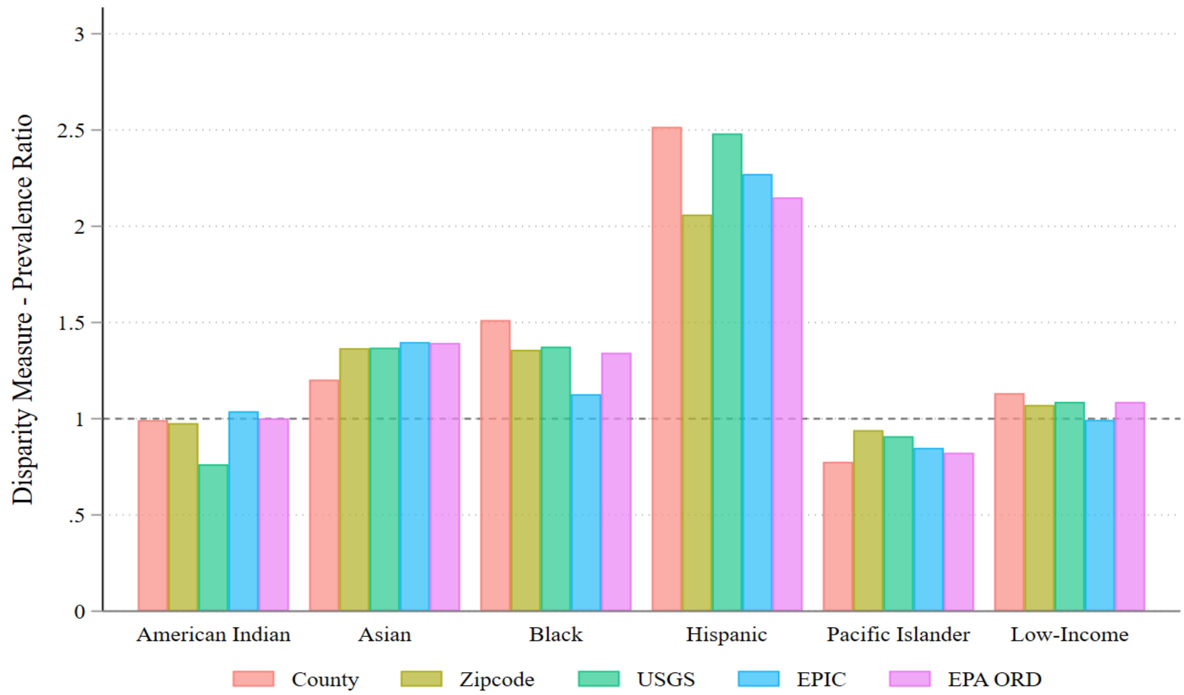
(c) Count of Unique PFAS Detected



(d) Sum of Average PFOA and PFOS Concentrations

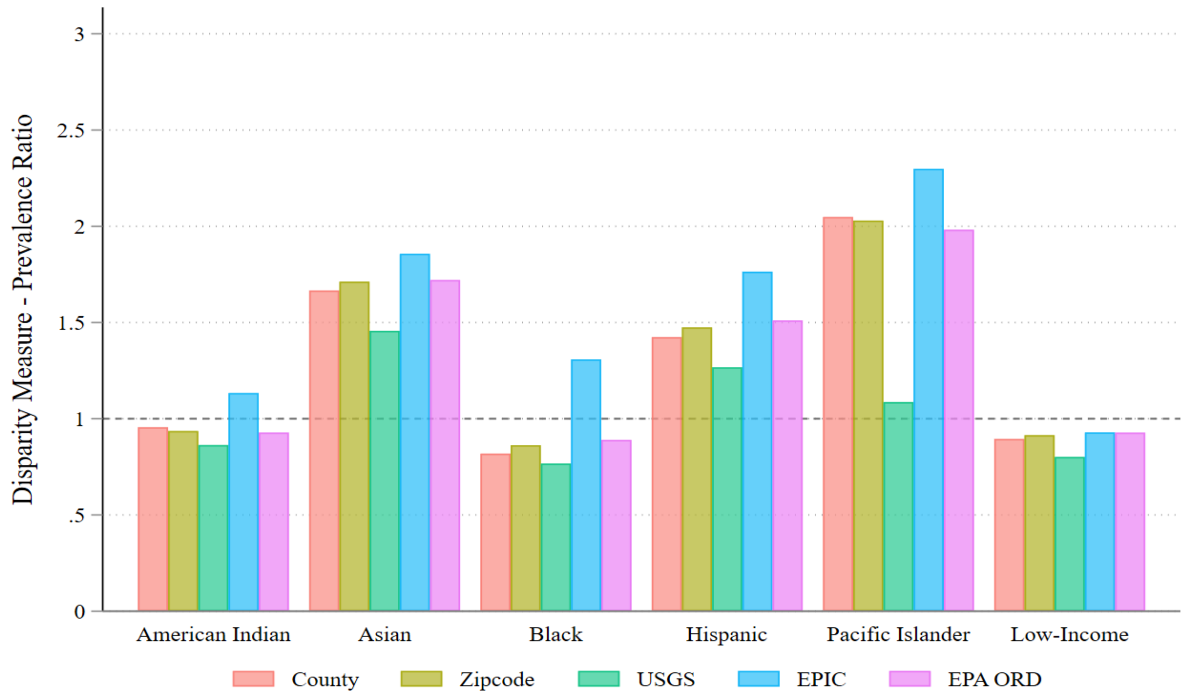
Notes: Figures present disparity measures according to alternative indicators for PFAS levels in drinking water including the sum of the maximum concentrations, the detection share, the count of unique PFAS species ever detected, and the sum of just average PFOA and PFOS concentrations. In all measures representing concentration totals, non-detects are inputted as zeroes.

Figure A9: PFAS Disparity Measure When Excluding all pre-2020 Samples



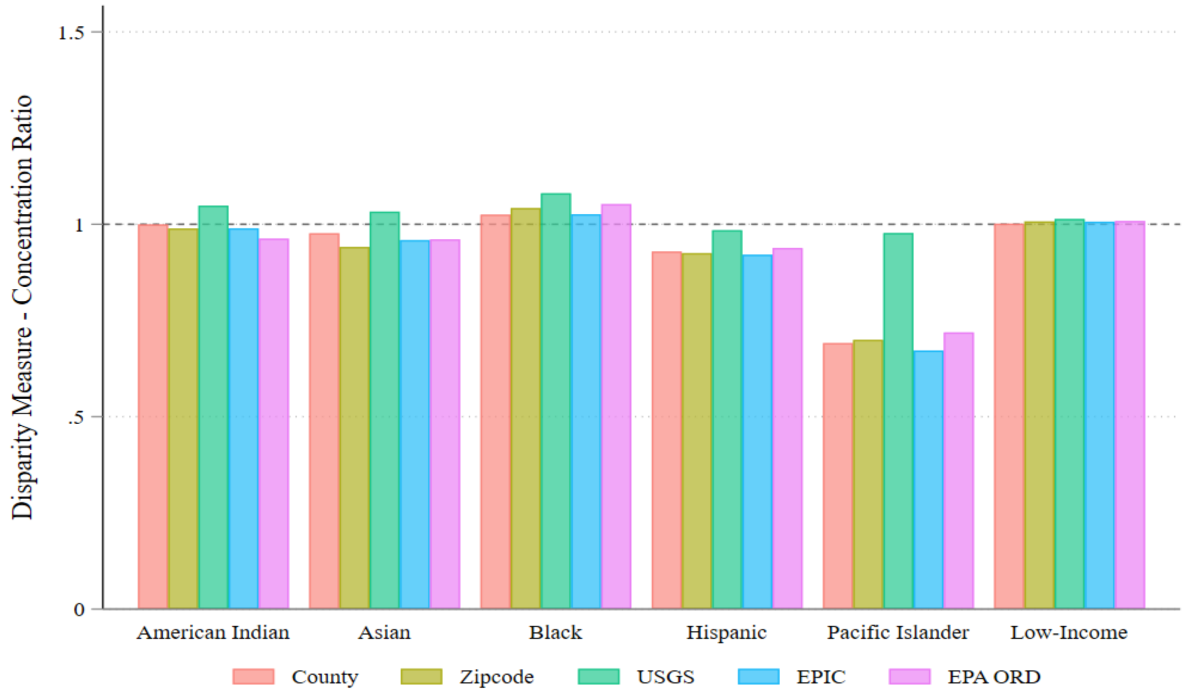
Notes: Figure presents disparity measures according to our primary indicator for PFAS levels in drinking water but excluding all sampling years prior to 2020. In earlier periods, PFAS sampling had higher detection thresholds and was more likely to be targeted to systems with known issues.

Figure A10: Disparity Measure with respect to the Total Count of PFAS Samples

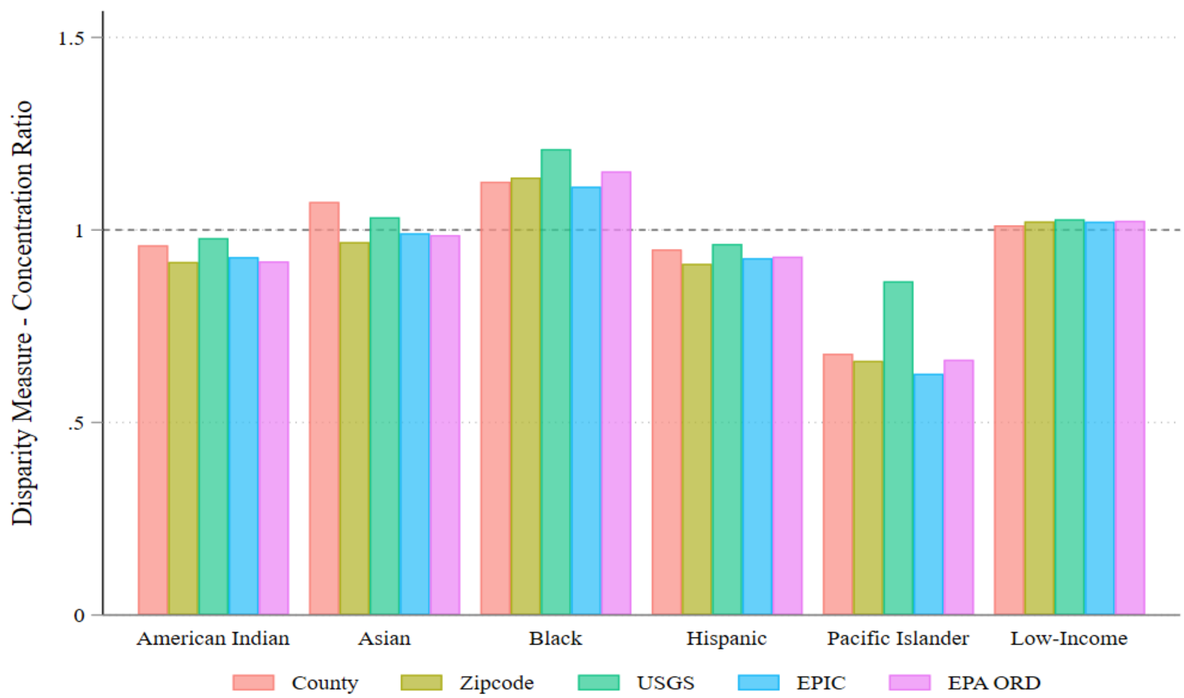


Notes: Figure presents disparities in the total count of PFAS samples collected across demographic groups.

Figure A11: Disparity Measures According to TTHM and HAA5



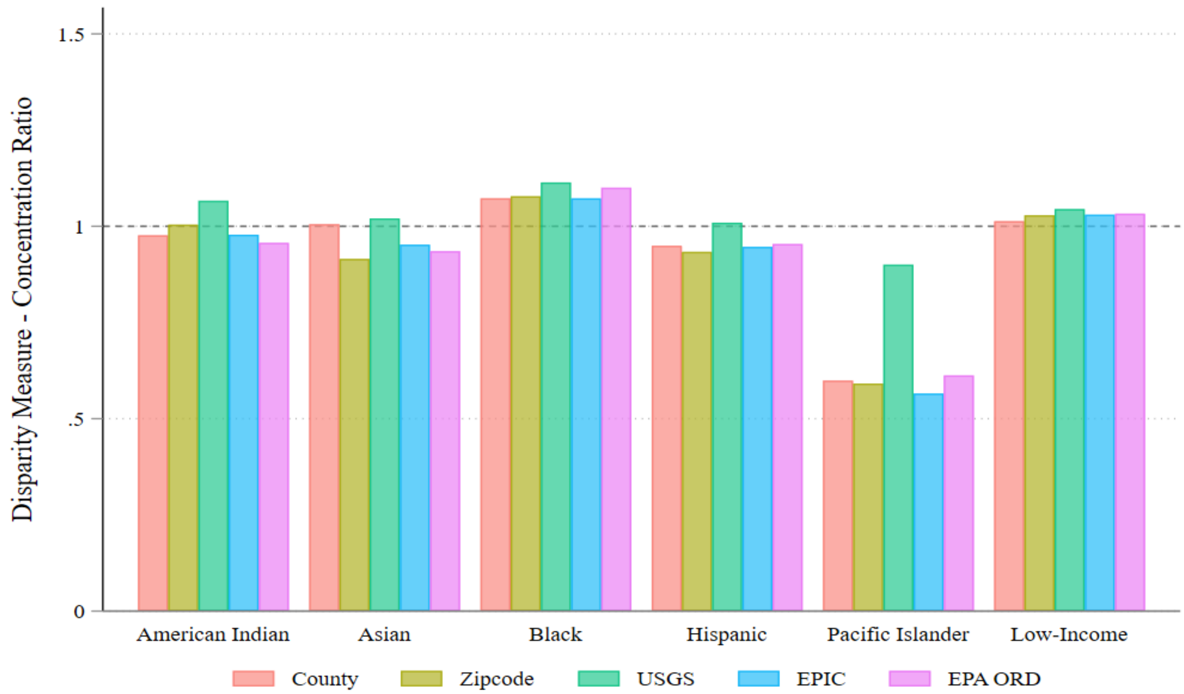
(a) TTHM Concentrations (2006-2019)



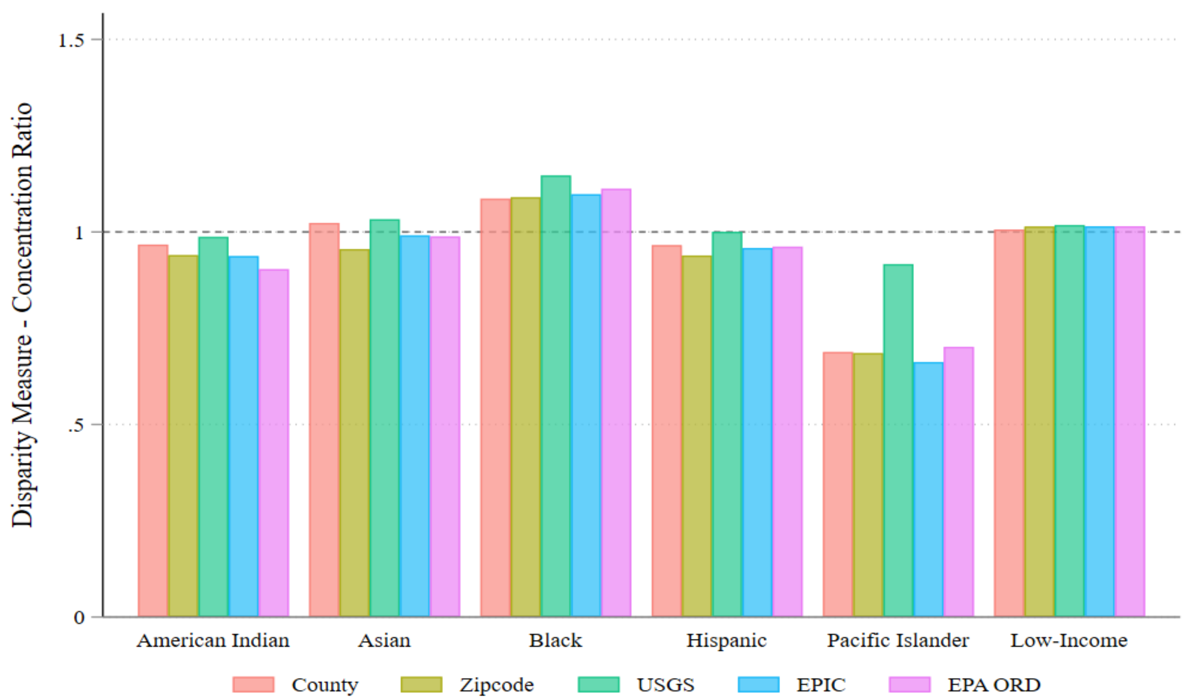
(b) HAA5 Concentrations (2006-2019)

Notes: Figures present disparity measures according to the disinfectant byproduct classes TTHM and HAA5.

Figure A12: DBP Disparity Measures According to Distinct Regulatory Time Horizons



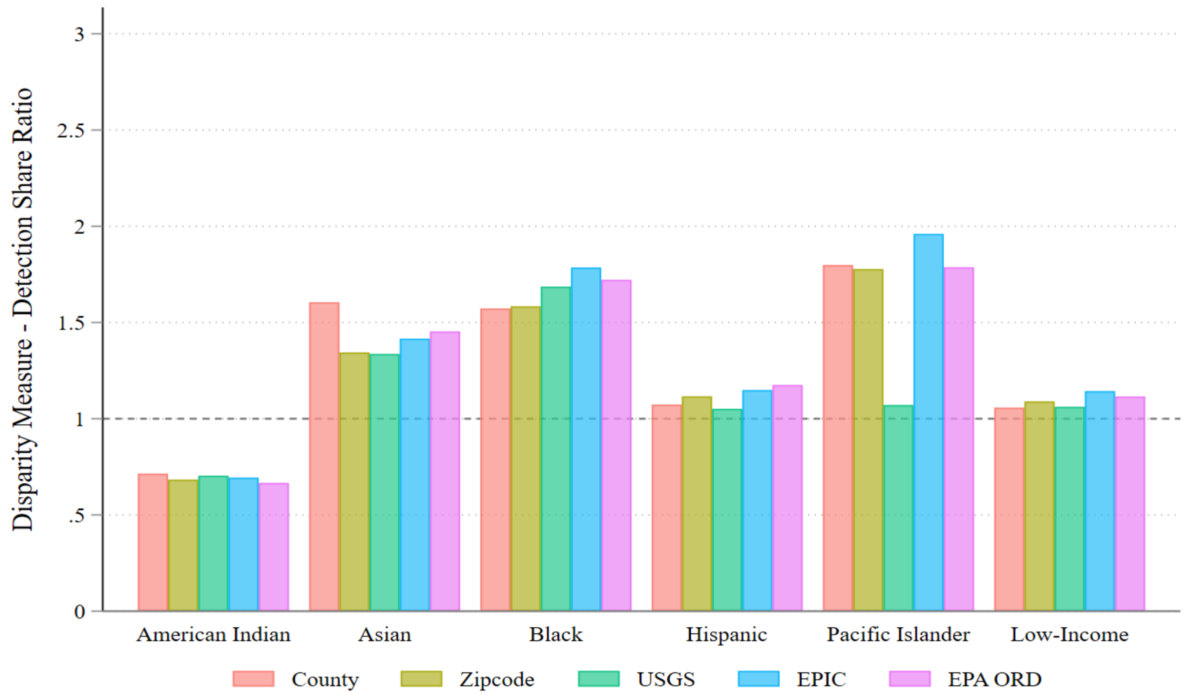
(a) Combined TTHM and HAA5 Concentrations (2006-2012)



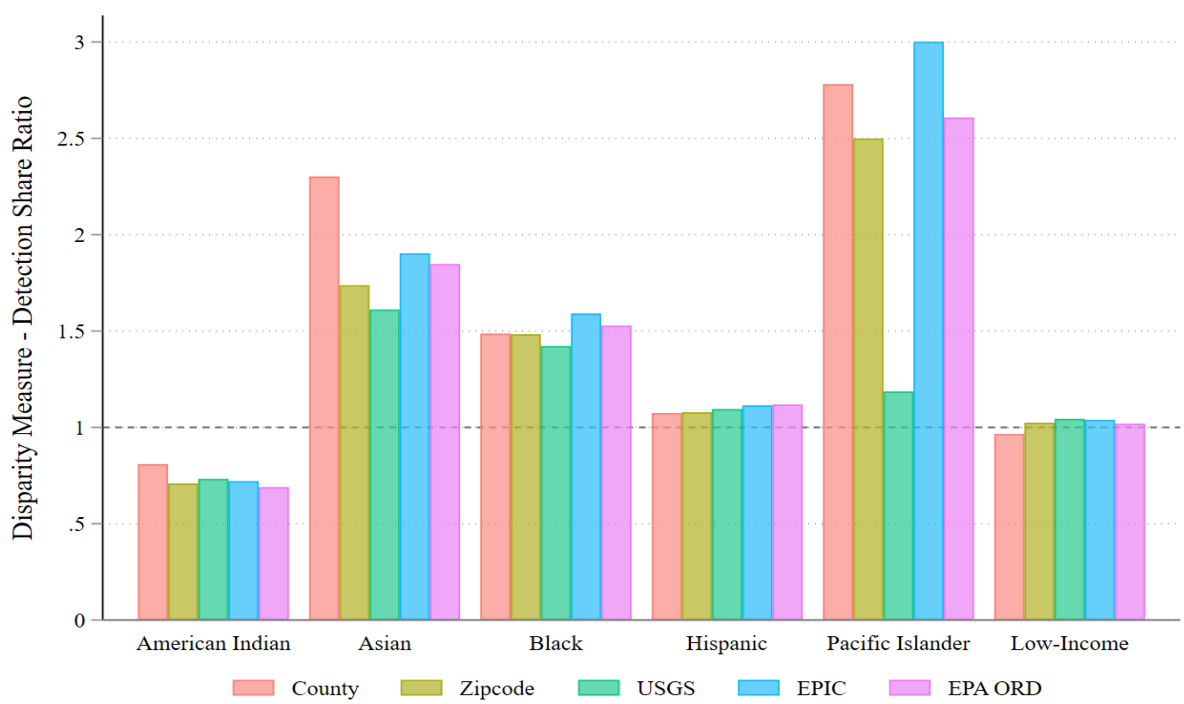
(b) Combined TTHM and HAA5 Concentrations (2013-2019)

Notes: Figures present disparity measures according to the combined concentrations of disinfectant byproduct classes TTHM and HAA5 across distinct analytic time periods. The period from 2006-2012 relates to samples collected as part of the Six Year Review 3, and the period from 2013-2019 relates to samples collected as part of the Six Year Review 4. Samples in Six Year Review 4 were collected under the latest set of regulatory requirements.

Figure A13: Total Coliform Disparity Measures According to Distinct Regulatory Time Horizons



(a) Total Coliform Detection Share (2006-2015)



(b) Total Coliform Detection Share (2016-2019)

Notes: Figures present disparity measures of total coliform detection shares across distinct time periods. The period from 2006-2015 relates to samples collected as part of the older Total Coliform Rule, and the period from 2016-2019 relates to samples collected as part of the Revised Total Coliform Rule.

Table A1: Disparity Measures by Service Area Type for EPIC Tier 1 and Tier 2 Systems

	County	Zip code	USGS	EPIC	EPA ORD
Health-based Violations (2015-2022)					
POC & NH White	0.98	1.04	1.04	1.07	1.08
Below & Above 2X Poverty Level	1.16	1.19	1.24	1.27	1.29
Lead Action Level Exceedences (1991-2021)					
POC & NH White	1.24	1.13	1.09	1.25	1.14
Below & Above 2X Poverty Level	0.91	0.99	0.97	1.01	0.96
PFAS Concentrations (2013-2023)					
POC & NH White	1.72	1.54	1.69	1.56	1.59
Below & Above 2X Poverty Level	1.09	1.03	1.03	0.97	1.03
TTHM HAA5 Concentrations (2006-2019)					
POC & NH White	1.02	1.00	1.07	1.02	1.03
Below & Above 2X Poverty Level	1.01	1.02	1.02	1.02	1.02
Total Coliform Detection Share (2006-2019)					
POC & NH White	1.37	1.30	1.25	1.39	1.34
Below & Above 2X Poverty Level	0.98	1.03	1.05	1.06	1.04
Arsenic Concentration (2006-2019)					
POC & NH White	1.35	1.39	1.21	1.29	1.36
Below & Above 2X Poverty Level	1.10	1.11	1.09	1.06	1.11
Nitrate Concentration (2006-2019)					
POC & NH White	1.22	1.28	1.10	1.23	1.27
Below & Above 2X Poverty Level	1.00	0.99	0.98	0.97	0.99
PWS Observations	45,934	10,223	18,806	45,372	44,415
Population Served	308m	283m	269m	308m	313m

Table displays the disparity metrics across the two groups listed in each row. TTHM & HAA5 Concentrations and Total Coliform Detection Share represent system-level average calculations for each chemical over the period 2006-2019, which are summed across TTHM and HAA5 to derive a total DBP concentration.

Table A2: Disparity Measures by Service Area Type for EPIC Tier 2 and Tier 3 Systems

	County	Zip code	USGS	EPIC	EPA ORD
Health-based Violations (2015-2022)					
POC & NH White	0.80	0.84	0.87	0.93	0.89
Below & Above 2X Poverty Level	1.08	1.11	1.12	1.20	1.17
Lead Action Level Exceedences (1991-2021)					
POC & NH White	1.57	1.49	1.34	1.46	1.54
Below & Above 2X Poverty Level	0.90	1.03	1.00	0.99	1.01
PFAS Concentrations (2013-2023)					
POC & NH White	2.52	1.99	2.21	2.04	2.12
Below & Above 2X Poverty Level	1.21	1.12	1.12	0.98	1.09
TTHM HAA5 Concentrations (2006-2019)					
POC & NH White	1.14	1.11	1.21	1.11	1.13
Below & Above 2X Poverty Level	1.03	1.05	1.03	1.04	1.03
Total Coliform Detection Share (2006-2019)					
POC & NH White	1.65	1.61	1.51	1.67	1.65
Below & Above 2X Poverty Level	0.96	1.03	1.05	1.03	1.02
Arsenic Concentration (2006-2019)					
POC & NH White	0.86	0.87	0.86	0.82	0.85
Below & Above 2X Poverty Level	1.03	1.06	1.09	0.97	1.05
Nitrate Concentration (2006-2019)					
POC & NH White	0.78	0.82	0.83	0.79	0.81
Below & Above 2X Poverty Level	0.94	0.92	0.92	0.93	0.93
Observations	6,760	1,287	3,304	6,710	6,602

Table displays the disparity metrics across the two groups listed in each row. TTHM & HAA5 Concentrations and Total Coliform Detection Share represent system-level average calculations for each chemical over the period 2006-2019, which are summed across TTHM and HAA5 to derive a total DBP concentration.

Table A3: Disparity Measures by Service Area Type for Five States with High-Quality Pre-delineated Service Areas

	County	Zip code	USGS	EPIC	EPA ORD
Health-based Violations (2015-2022)					
POC & NH White	1.34	1.29	1.37	1.62	1.63
Below & Above 2X Poverty Level	1.23	1.29	1.46	1.57	1.57
Lead Action Level Exceedences (1991-2021)					
POC & NH White	1.06	1.01	1.06	1.11	1.11
Below & Above 2X Poverty Level	0.91	0.92	0.97	0.93	0.93
PFAS Concentrations (2013-2023)					
POC & NH White	1.08	1.22	1.15	1.20	1.19
Below & Above 2X Poverty Level	0.99	1.01	0.95	1.01	1.02
TTHM HAA5 Concentrations (2006-2019)					
POC & NH White	0.98	0.95	1.00	0.98	0.98
Below & Above 2X Poverty Level	0.91	0.90	0.93	0.92	0.91
Total Coliform Detection Share (2006-2019)					
POC & NH White	1.04	1.22	1.04	0.97	1.03
Below & Above 2X Poverty Level	1.13	1.06	1.05	1.05	1.10
Arsenic Concentration (2006-2019)					
POC & NH White	1.32	1.29	1.14	1.29	1.30
Below & Above 2X Poverty Level	1.24	1.25	1.21	1.26	1.26
Nitrate Concentration (2006-2019)					
POC & NH White	1.43	1.41	1.32	1.42	1.42
Below & Above 2X Poverty Level	1.14	1.09	1.11	1.10	1.10
Observations	28,266	5,904	8,874	27,845	25,267

Table displays the disparity measures across the two groups listed in each row. Sample includes water systems in California, Connecticut, New Jersey, New Mexico, and Washington. TTHM & HAA5 Concentrations and Total Coliform Detection Share represent system-level average calculations for each chemical over the period 2006-2019, which are summed across TTHM and HAA5 to derive a total DBP concentration.

Table A4: Summary Statistics across all Water Systems with Non-Zero Drinking Water Quality Measures

Boundary	Mean	Median	Max	CWS	Total Pop.
Health-based Violations (2015-2022)					
County	5.910	2.000	366.0	10,506	80M
Zip Code	4.710	2.000	366.0	2,835	74M
USGS	6.141	2.000	366.0	4,823	70M
EPIC	5.863	2.000	366.0	10,509	80M
EPA ORD	5.831	2.000	366.0	10,254	81M
Lead Action Level Exceedences (1991-2021)					
County	2.079	1.000	40.0	10,008	93M
Zip Code	2.511	1.500	40.0	2,870	89M
USGS	2.015	1.000	34.0	4,171	92M
EPIC	2.077	1.000	40.0	9,962	93M
EPA ORD	2.090	1.000	40.0	9,683	96M
PFAS Concentration (2013-2023)					
County	17.064	7.200	1,020.5	3,237	120M
Zip Code	17.796	7.128	1,020.5	2,972	120M
USGS	18.417	6.594	1,020.5	1,850	110M
EPIC	17.028	7.203	1,020.5	3,221	120M
EPA ORD	17.089	7.200	1,020.5	3,244	120M
TTHM & HAA5 Concentrations (2006-2019)					
County	37.129	23.400	661.9	24,602	280M
Zip Code	44.330	42.503	314.5	8,460	260M
USGS	34.602	21.100	585.2	11,148	250M
EPIC	37.093	23.286	661.9	24,582	280M
EPA ORD	36.923	23.356	661.9	23,874	280M
Total Coliform Detection Share (2006-2019)					
County	0.027	0.012	0.5	27,595	220M
Zip Code	0.025	0.006	0.5	7,075	200M
USGS	0.026	0.010	0.5	11,961	190M
EPIC	0.027	0.012	0.5	27,559	220M
EPA ORD	0.027	0.012	0.5	26,537	220M
Arsenic Concentration (2006-2019)					
County	1.672	0.837	246.7	15,240	140M
Zip Code	1.378	0.530	73.8	3,678	130M
USGS	1.632	0.815	62.5	7,869	140M
EPIC	1.674	0.850	246.7	15,253	130M
EPA ORD	1.683	0.850	246.7	14,967	140M
Nitrate Concentration (2006-2019)					
County	1.085	0.340	300.1	31,251	250M
Zip Code	0.967	0.349	15.5	9,015	240M
USGS	1.137	0.356	60.9	15,226	250M
EPIC	1.084	0.340	300.1	31,172	250M
EPA ORD	1.086	0.340	300.1	30,413	260M

Table A5: Demographic Regression Results According to the EPIC Boundaries

	Health-based	Lead	PFAS	DBP	TCR	ARS	NITR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% American Indian	6.243***	0.167*	2.313	1.646	0.007***	0.892***	−0.178
	(0.401)	(0.093)	(6.557)	(2.585)	(0.003)	(0.167)	(0.201)
% Asian	−5.201***	0.646***	16.341***	−43.615***	0.001	0.374	1.634***
	(0.666)	(0.154)	(4.808)	(4.279)	(0.005)	(0.289)	(0.335)
% Black	−0.381*	−0.059	4.688**	−0.046	−0.005***	−0.754***	−1.098***
	(0.208)	(0.048)	(1.848)	(1.231)	(0.001)	(0.088)	(0.105)
% Hispanic	2.732***	−0.262***	7.891***	−15.057***	−0.013***	1.741***	1.518***
	(0.181)	(0.042)	(1.606)	(1.180)	(0.001)	(0.076)	(0.089)
% Pacific Islander	−1.697	−0.061	−82.004**	−17.545	0.124***	−0.449	−0.952
	(2.360)	(0.545)	(38.222)	(13.193)	(0.015)	(0.988)	(1.188)
% Low income^{+}	1.844***	−0.291***	−8.064***	19.643***	0.009***	−0.131	−0.242**
	(0.205)	(0.047)	(1.855)	(1.326)	(0.001)	(0.088)	(0.104)
Tribal System	−2.245***	−0.049	−2.062	−9.345***	0.005**	0.428***	−0.206
	(0.338)	(0.078)	(4.595)	(2.146)	(0.002)	(0.142)	(0.170)
Large system^{++}	−0.640***	0.188***	−0.585	−1.194*	0.014***	−0.087	0.068
	(0.127)	(0.029)	(0.651)	(0.704)	(0.001)	(0.056)	(0.066)
Small system	0.388***	−0.043*	−2.236***	−0.257	0.0001	0.040	0.128**
	(0.100)	(0.023)	(0.779)	(0.565)	(0.001)	(0.044)	(0.052)
Very Large system	−1.363***	0.406***	2.861**	−2.897*	0.046***	−0.072	0.130
	(0.296)	(0.068)	(1.333)	(1.595)	(0.002)	(0.123)	(0.145)
Very small system	0.390***	−0.063***	−1.020	−6.167***	0.008***	0.130***	0.243***
	(0.096)	(0.022)	(0.755)	(0.566)	(0.001)	(0.042)	(0.050)
Groundwater	−1.592***	−0.202***	−0.670	−45.429***	0.005***	0.326***	0.071*
	(0.071)	(0.016)	(0.559)	(0.408)	(0.0005)	(0.037)	(0.042)
Constant	1.491***	0.743***	6.993***	59.287***	0.008***	0.199***	0.597***
	(0.112)	(0.026)	(0.808)	(0.662)	(0.001)	(0.052)	(0.061)
Observations	45,492	45,492	10,932	30,448	39,508	38,128	38,943

Notes: *p<0.1; **p<0.05; ***p<0.01. % Low income refers to the % of the population served with incomes below twice the Federal Poverty Level. System size categories are based on the population served by the system, where medium-sized systems are the omitted category. Very small systems serve fewer than 500 individuals, small systems serve 501-3,300, large systems serve 10,000 to 100,000, and very large systems serve over 100,000 people.

Table A6: Environmental Burden Regression Results According to the EPIC Boundaries

	(1) Health Violations	(2) Lead ALEs	(3) PFAS Conc.	(4) DBP Conc.	(5) Coliform Detections	(6) Arsenic Conc.	(7) Nitrates Conc.
Lead Paint	1.380***	−0.073	−0.208***	20.466***	0.001	0.160***	0.269***
	(0.015)	(0.163)	(0.066)	(1.468)	(0.002)	(0.052)	(0.071)
Ozone	−0.029***	0.082***	0.027***	−0.185***	0.0002*	0.0001	0.035***
	(0.001)	(0.008)	(0.003)	(0.067)	(0.0001)	(0.002)	(0.003)
$PM_{2.5}$	−0.074***	−0.078**	0.120***	−0.360	−0.0002	−0.012	0.046***
	(0.003)	(0.031)	(0.013)	(0.264)	(0.0004)	(0.008)	(0.011)
Toxic Release Facility	−0.222***	−0.002	0.016***	0.784***	0.001***	−0.032***	0.002
	(0.004)	(0.024)	(0.005)	(0.191)	(0.0003)	(0.007)	(0.009)
Wastewater discharge	−0.0002***	−0.0004	0.00002	−0.0004	−0.00000	−0.00003*	0.00003*
	(0.00003)	(0.001)	(0.00003)	(0.0004)	(0.00000)	(0.00002)	(0.00002)
Superfund Site	−0.135***	−0.049	0.329***	−1.774	−0.002	−0.061	0.355***
	(0.020)	(0.150)	(0.036)	(1.329)	(0.002)	(0.054)	(0.072)
Constant	3.735***	−23.290	−1.434***	11.584	0.016	2.810**	−1.032
	(0.410)	(9,426.608)	(0.152)	(37.853)	(0.056)	(1.184)	(1.703)
State control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,635	34,635	8,394	27,438	27,138	42,320	22,184

Notes: *p<0.1; **p<0.05; ***p<0.01. Each row represents a specific EJSCREEN environmental indicator. These include potential community-level exposure to lead paint, ozone levels, fine particulate matter, proximity to hazardous waste sites, wastewater discharge, and superfund site proximity.

Table A7: Demographic Regression Results According to the County served

	Health-based	Lead	PFAS	DBP	TCR	ARS	NITR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% American Indian	6.829***	0.353***	8.791	−0.172	0.003	0.438**	−0.795***
	(0.485)	(0.111)	(7.543)	(3.086)	(0.003)	(0.199)	(0.239)
% Asian	−8.166***	1.937***	29.751***	−45.099***	0.011	0.575	3.608***
	(0.965)	(0.220)	(7.316)	(6.286)	(0.008)	(0.411)	(0.482)
% Black	−0.325	−0.171***	7.554***	2.286	−0.011***	−1.277***	−2.003***
	(0.268)	(0.061)	(2.422)	(1.588)	(0.002)	(0.112)	(0.134)
% Hispanic	3.805***	−0.300***	7.557***	−16.023***	−0.018***	2.403***	1.544***
	(0.213)	(0.049)	(1.931)	(1.389)	(0.002)	(0.089)	(0.105)
% Pacific Islander	12.813**	−7.656***	−178.648***	5.990	0.328***	−1.512	−8.722***
	(5.685)	(1.297)	(50.697)	(32.763)	(0.038)	(2.354)	(2.811)
% Low income+	4.776***	−0.604***	−16.719***	37.176***	0.018***	0.272*	0.342*
	(0.375)	(0.086)	(3.188)	(2.345)	(0.003)	(0.159)	(0.190)
Tribal System	−0.876	0.157	−4.854	−11.761***	0.004	1.449***	−0.325
	(0.582)	(0.133)	(10.164)	(4.019)	(0.004)	(0.247)	(0.295)
Large system++	−0.536***	0.159***	−0.854	−0.803	0.014***	−0.080	0.068
	(0.129)	(0.029)	(0.651)	(0.702)	(0.001)	(0.056)	(0.066)
Small system	0.364***	−0.037	−2.401***	−0.392	0.0001	0.037	0.124**
	(0.101)	(0.023)	(0.779)	(0.564)	(0.001)	(0.044)	(0.052)
Very Large system	−1.172***	0.343***	2.636**	−2.630*	0.046***	−0.068	0.147
	(0.297)	(0.068)	(1.322)	(1.581)	(0.002)	(0.122)	(0.144)
Very small system	0.374***	−0.064***	−1.245*	−5.926***	0.008***	0.092**	0.198***
	(0.097)	(0.022)	(0.756)	(0.564)	(0.001)	(0.042)	(0.049)
Groundwater	−1.576***	−0.201***	−0.575	−45.605***	0.005***	0.361***	0.127***
	(0.072)	(0.016)	(0.560)	(0.410)	(0.0005)	(0.037)	(0.042)
Constant	0.400***	0.841***	9.081***	53.678***	0.006***	−0.008	0.399***
	(0.153)	(0.035)	(1.159)	(0.923)	(0.001)	(0.067)	(0.079)
Observations	45,600	45,600	10,956	30,460	39,589	38,209	39,035

Notes: *p<0.1; **p<0.05; ***p<0.01. % Low income refers to the % of the population served with incomes below twice the Federal Poverty Level. System size categories are based on the population served by the system, where medium-sized systems are the omitted category. Very small systems serve fewer than 500 individuals, small systems serve 501-3,300, large systems serve 10,000 to 100,000, and very large systems serve over 100,000 people.

Table A8: Environmental Burden Regression Results According to the County served

	Health-based	Lead	PFAS	DBP	TCR	ARS	NITR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lead Paint	0.293***	1.179***	−11.444***	17.242***	−0.002*	0.094	1.394***
	(0.029)	(0.047)	(1.729)	(1.527)	(0.001)	(0.084)	(0.101)
Ozone	0.043***	0.004***	−0.064	−0.219***	−0.0002***	0.039***	0.046***
	(0.001)	(0.001)	(0.041)	(0.037)	(0.00003)	(0.002)	(0.002)
$PM_{2.5}$	0.141***	−0.057***	−0.319**	1.647***	−0.002***	0.045***	0.036***
	(0.002)	(0.004)	(0.153)	(0.150)	(0.0001)	(0.007)	(0.009)
Toxic Release Facility	−0.325***	0.133***	1.102***	−0.083	0.002***	0.066***	0.109***
	(0.007)	(0.003)	(0.184)	(0.224)	(0.0002)	(0.012)	(0.014)
Wastewater discharge	−0.001***	0.0002***	−0.001	−0.003*	−0.00001**	−0.0001	0.001***
	(0.0001)	(0.00004)	(0.002)	(0.002)	(0.00000)	(0.0001)	(0.0001)
Superfund Site	−2.199***	0.444***	12.217***	−27.399***	−0.003	−0.668***	0.410***
	(0.061)	(0.059)	(2.076)	(2.286)	(0.002)	(0.122)	(0.145)
Constant	−2.394***	−0.997***	10.969***	23.549***	0.042***	−1.325***	−1.826***
	(0.031)	(0.057)	(1.938)	(1.953)	(0.002)	(0.093)	(0.112)
Observations	45,190	45,190	10,838	29,992	38,930	37,544	38,372

Notes: *p<0.1; **p<0.05; ***p<0.01. Each row represents a specific EJSCREEN environmental indicator. These include potential community-level exposure to lead paint, ozone levels, fine particulate matter, proximity to hazardous waste sites, wastewater discharge, and superfund site proximity.