Inequities in Drinking Water Quality Among Domestic Well Communities and Community Water Systems, California, 2011–2019

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See also Levy and Hernández, p. 48.

Objectives. To evaluate universal access to clean drinking water by characterizing relationships between community sociodemographics and water contaminants in California domestic well areas (DWAs) and community water systems (CWSs).

Methods. We integrated domestic well locations, CWS service boundaries, residential parcels, building footprints, and 2013–2017 American Community Survey data to estimate sociodemographic characteristics for DWAs and CWSs statewide. We derived mean drinking and groundwater contaminant concentrations of arsenic, nitrate, and hexavalent chromium (Cr[VI]) between 2011 and 2019 and used multivariate models to estimate relationships between sociodemographic variables and contaminant concentrations.

Results. We estimated that more than 1.3 million Californians (3.4%) use domestic wells and more than 370 000 Californians rely on drinking water with average contaminant concentrations at or above regulatory standards for 1 or more of the contaminants considered. Higher proportions of people of color were associated with greater drinking water contamination.

Conclusions. Poor water quality disproportionately impacts communities of color in California, with the highest estimated arsenic, nitrate, and Cr(VI) concentrations in areas of domestic well use. Domestic well communities must be included in efforts to achieve California's Human Right to Water.
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Drinking water crises in Flint, Michigan,[1] and Newark, New Jersey,[2] have highlighted the lack of universal access to safe drinking water in the United States. Roughly 10% of California's public drinking water systems are currently out of compliance with state drinking water quality standards, and an estimated 6 million Californians are served by systems that have been in violation at some point since 2012.[3] A disproportionate number of water quality violations in the state occur in smaller drinking water systems that serve rural, low-income communities, where degraded infrastructure and a lack of resources make it challenging to meet regulatory standards.[4–8] Communities served by water systems with elevated contaminant levels are disproportionately poor and Latinx, raising environmental justice concerns.[6,7,9]

In 2012, California passed Assembly Bill 685,[10] known as the Human Right to Water law, which recognizes the universal right to clean, safe, affordable drinking water for all, including communities served by community water systems (CWSs, defined as systems with at least 15 service connections or serving at least 25 year-round residents), state small water systems (5–14 service connections), and domestic wells and small systems (< 5 service connections; referred to herein as "domestic wells").[11] One barrier to achieving universal access to clean drinking water is lack of information on the location of domestic wells, which fall outside the purview of state and federal drinking water regulations.[12,13] Communities served by domestic wells often face significant water-quality challenges compared with CWSs as domestic wells commonly serve rural, agricultural, and socioeconomically disadvantaged communities.[14] While CWSs are required to monitor for select drinking water contaminants under the Safe Drinking Water Act, monitoring of domestic wells is unregulated.

In this analysis, we provided a fine-scale estimate of the locations of domestic well communities in California and estimated groundwater quality in those areas and in delivered water from CWSs. We characterized relationships between community sociodemographics and water quality among both domestic well and CWS populations. We did not differentiate state small water systems from domestic well areas because of the paucity of data on these systems' locations. We focused on 3 chemical contaminants selected because of evidence of statewide prevalence and toxicity:[4,9,15] arsenic, nitrate, and hexavalent chromium (Cr[VI]). Each of these contaminants can cause significant health effects.[16–18] Arsenic occurs naturally in groundwater, and concentrations increase with land subsidence from industrial and agricultural activities.[19,20] Nitrate contamination is common in agricultural regions because of fertilizer runoff and industrial animal operations.[21] Cr(VI) enters groundwater from industrial and manufacturing activities.[22]

METHODS

We combined multiple secondary data sources to identify drinking water sources, estimate the drinking water quality and characteristics of communities served, and estimate associations between average contaminant concentrations and community sociodemographic variables.

Community Water Systems

We obtained service area boundaries from the Tracking California Drinking Water Systems Geographic Reporting Tool[23] for CWSs listed as active in California's Safe Drinking Water Information System as of 2018.[24] We removed duplicates and assigned any overlapping service areas to the CWS with the smaller service area because smaller systems were often entirely within larger systems' boundaries. We excluded service area boundaries for wholesale water systems that do not directly serve consumers, but included water purchased from wholesalers in our water quality estimates.

Domestic Well Areas

We obtained records for more than 900 000 wells drilled in California between 1927 and 2018 from the Department of Water Resources' Online System for Well Completion Reports.[25] Most well locations were reported by the Public Land Survey System (PLSS) section (a roughly 1 × 1 mile square) within which they were located, so we approximated their spatial coordinates using the corresponding PLSS section centroid. We retained more precise location information for a small subset of wells with records that reported latitude and longitude with an estimated accuracy of within 50 feet of the true coordinates.[25]

To identify domestic well areas (DWAs), we excluded unpopulated Census blocks according to the 2010 decennial Census. We excluded PLSS sections without wells and PLSS sections entirely within the boundary of a CWS (which assumes domestic wells within a CWS service area were not in use). We used a high-resolution, statewide map of populated areas created via dasymetric mapping to refine DWA locations by excluding unpopulated space within geographic Census unit boundaries.[26] This population layer was created by using (1) 2010 decennial Census (block boundaries and population totals) and 2013–2017 American Community Survey (ACS) data (block group population totals), (2) a statewide database of residential parcel boundaries,[27] and (3) a building footprints layer developed by Microsoft.[28]

For each Census block, we used spatial downscaling methods to disaggregate population values to subblock geometries. In method 1, residential parcels were identified from the parcel data set and used as the boundaries of populated areas within each block. This assumes populations are uniformly distributed across residential parcels rather than across the entire block. This technique was applied to Census blocks containing 91.8% of the state's population. In method 2, for populated Census blocks that did not contain residential parcels, individual building boundaries within the block were identified using Microsoft's building footprint data set. This assumes that for blocks with a nonzero population but with no residential parcels, population is uniformly distributed among the buildings within these blocks. This method was applied to blocks containing 7.9% of the state's population. For the blocks containing the remaining 0.3% of the state's population, with neither residential parcels nor building footprints, no downscaling was applied, with the assumption that those populations are uniformly distributed across the entire block area. The result was a statewide map of populated areas downscaled within Census blocks. This map was intersected with PLSS sections to create our final geographic units of analysis: 1914 populated portions of Census block groups served by domestic wells (Figure 1).

Sociodemographic and Population Variables

We derived population estimates for DWAs and CWSs by using the 2010 decennial Census and the 2013–2017 ACS. Population estimates at the block level were last enumerated in the 2010 decennial Census, with values at the parent block-group level updated annually via the ACS. For data vintage consistency, we scaled block-level population values according to population growth rates observed in parent block groups between 2010 and the 2013–2017 ACS. These block populations were assigned to the reduced block populated area boundaries identified via dasymetric mapping as described previously.

To assign population estimates to DWAs and CWSs, we summed the population within each populated area in each block. Because CWSs commonly encompass many blocks, we aggregated the population from each block to CWSs. This approach distributes the population in Census blocks that serve both DWAs and CWSs to their respective water systems without double counting population and assigns 98.8% of the total Census population a water source (Figure A, available as a supplement to the online version of this article at http://www.ajph.org).

Sociodemographic characteristics expressed as mean or median values (not counts) were assigned to populated areas using 2013–2017 ACS block-group level value, with a parent block group's value applying equally to all of its blocks. To calculate the value of these characteristics for DWAs and CWSs, we derived weighted averages using the population contribution of each Census block within the CWS or DWA boundary relative to the total CWS or DWA population as the weights:[29]

$$W = \frac{\sum_{i}^{n} w_i X_i}{\sum_{i}^{n} w_i} \qquad (1)$$

where W is the weighted average sociodemographic variable for the CWS or DWA, w_i is the population weight for Census block group i intersecting with the CWS or DWA, and X_i is the sociodemographic variable from Census block group i. For blocks with populated areas spanning multiple CWS or DWA boundaries, population was allocated based on an area-weighted apportionment of populated area within that block.

Water Quality

We used water quality data compiled by the California Environmental Protection Agency Office of Environmental Health Hazard Assessment (OEHHA) for CalEnviroScreen4.0, a spatial screening tool to identify communities disproportionately burdened by pollution and social stressors.[30] To assess drinking water quality, OEHHA combined data from the State Water

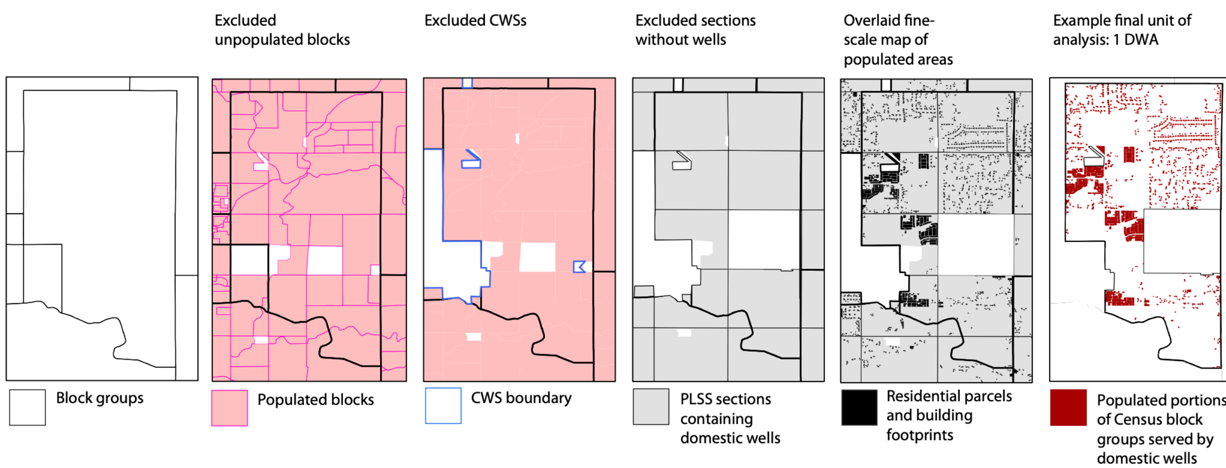

FIGURE 1— Schematic of Method for Identifying Domestic Well Areas (DWAs) in California

Note. CWS = community water system; PLSS = Public Land Survey System.

Resources Control Board's Water Quality Monitoring database over the most recent regulatory compliance cycle (2011–2019) to calculate a 9-year average for each water system. This enables comparisons between systems with different monitoring frequencies and across DWAs where sampling data are sparse. Contaminant values were time weighted and averaged across sources (including water purchased from wholesalers) for each CWS to represent estimated delivered water quality over the study period. Observations below the detection limit were replaced with zero.

DWA water quality estimates were also obtained from OEHHA, which time-weighted water quality samples from the State Water Resources Control Board's Groundwater Ambient Monitoring and Assessment program, and averaged these estimates for 2011 to 2019. Nondetects were treated similarly to those in the CWS data set. These concentrations were then averaged across all wells within a block group and assigned to DWAs by block group identifier.

Statistical Analysis

We calculated descriptive statistics for water quality and sociodemographic characteristics for DWAs and CWSs separately, stratified by the number of service connections (for CWSs) and region. We then used generalized additive models[31] to estimate associations between contaminant concentrations and sociodemographic characteristics across individual CWS and DWA observations. We ran models separately for DWAs and CWSs. Our outcome for each contaminant was a mean concentration of at least one half of the California maximum contaminant level (MCL), which was selected because MCLs are established considering financial and technical feasibility and are not always health protective.[32] We considered using the public health goal to derive our outcome measure, as this benchmark reflects concentrations that pose no significant health risk if consumed for a lifetime.[33] However, the public health goal was below the limit of detection for our contaminants and could not be reliably measured. Because Cr(VI) does not currently have an MCL in California, we used the rescinded MCL value (as of 2017), which is being revised.[34]

We also derived a continuous outcome of a cumulative water contaminant index:[35]

$$CCI_i = \sum_{i}^{n} C_i \Big/ \frac{1}{2} MCL_i \qquad (2)$$

where C_i is the 2011–2019 mean concentration, and MCL_i is the MCL for contaminant *i*. We conducted a sensitivity analysis in which we dichotomized outcome measures based on the detection limit rather than the one half MCL. MCLs, public health goals, and detection limits for all contaminants are shown in Table A (available as a supplement to the online version of this article at http://www.ajph.org).

Our models included the following independent variables: race/ethnicity (% non-Latinx White, % Latinx, and % non-Latinx people of color, which included all other races and ethnicities), and housing tenure (% renters). We lacked sufficient sample size to reliably derive effect estimates for more specific racial groups in our models while also controlling for region. We considered measures of linguistic isolation and poverty, but did not include them because of their collinearity with race/ethnicity and housing tenure (Pearson correlation coefficients = 0.43–0.87). We scaled continuous predictors by 10%. To account for underlying regional differences in groundwater arsenic and nitrate concentrations, we adjusted for region following definitions used in previous studies[36,37] (Figure B and Table B, available as supplements to the online version of this article at http://www.ajph.org). We omitted region from Cr(VI) models because it is a more localized contaminant. Models of CWSs controlled for water source (any groundwater vs exclusively surface water) and system size (15–199 vs ≥ 200 service connections) as an indicator of technical, managerial, and financial capacity.[6] Models of DWAs controlled for population density.

We adjusted for the DWA or CWS centroid coordinates to account for spatial autocorrelation by fitting smoothing parameters consisting of 2 or more piecewise polynomial functions (or splines) to model terms for latitude and longitude. We similarly included smoothing parameters for population density in DWA models to account for nonlinear relationships.[38] We used Moran's I to assess residuals for spatial autocorrelation.[39,40] All models reached full convergence, indicating an appropriate number of parameters. We examined model residuals for normality, diagnostic plots, and the K index to verify adequate basis dimensions. Estimates were stable, and fit was not improved (assessed with Akaike information criterion) by increasing the number of nodes.

For dichotomous outcomes, we specified a binomial distribution with logit link function to estimate prevalence ratios (PRs).[41] We used a Gaussian distribution with an identity link function for the cumulative contaminant index.[31] We conducted data processing in ArcGIS version 10.7.1 (ESRI, Redlands, CA). We conducted statistical analyses in R version 3.5.3 (R Foundation, Vienna, Austria).[42]

RESULTS

We estimate that 37 million Californians are served by 2851 active CWSs. Mean contaminant concentrations exceeded the MCL for at least 1 contaminant for 0.6% of the population served by CWSs (216 306 people). An estimated 1.3 million people are served by the 1914 DWAs in our analysis, and 12.1% of the population (157 367 people) use domestic wells in areas with mean groundwater concentrations exceeding the MCL for 1 or more contaminants (Table 1). We observed elevated arsenic and nitrate concentrations among CWSs and DWAs in the San Joaquin Valley, where more people were served water exceeding the MCL for these 2 contaminants than in any other region (Tables C and D, available as supplements to the online version of this article at http://www.ajph.org). The proportion of people of color and renters with water exceeding the MCLs were more often higher than the statewide average in the San Joaquin Valley, Imperial Valley and Mojave Desert, and Central Coast (Tables C and D).

Our multivariate analysis found that, among CWSs, a 10% increase in the Latinx population was associated with a 14%, 21%, and 31% increase in the likelihood of elevated arsenic, nitrate, and Cr(VI), respectively (PR = 1.14; 95% confidence interval [CI] = 1.06, 1.22 for arsenic; PR = 1.21; 95% CI = 1.12, 1.30 for nitrate; and PR = 1.31; 95% CI = 1.21, 1.43 for Cr[VI]); and a 0.11 unit increase in cumulative contaminant index (mean difference = 0.11; 95% CI = 0.08, 0.14; Table 2). A 10% increase in non-Latinx people of color was associated with a 31% increase in the likelihood of elevated nitrate (PR = 1.31; 95% CI = 1.15, 1.49), a 28% increase in the likelihood of elevated Cr(VI) (PR = 1.28; 95% CI = 1.12, 1.46), and a 0.07 unit increase in cumulative contaminant index (mean difference = 0.07; 95% CI = 0.02, 0.12); we saw little evidence of an association with arsenic (Table 2). There was no association between percentage of renters and likelihood of elevated contaminant concentrations among CWSs. Small system size and groundwater reliance were associated with elevated chemical concentrations. We observed statistically significant differences in cumulative contaminant index by region.

Among DWAs, a 10% increase in the Latinx population was associated with a 13%, 19%, and 23% increase in the likelihood of elevated nitrate, arsenic, and Cr(VI), respectively (PR = 1.13; 95% CI = 1.05, 1.21 for nitrate; PR = 1.19; 95% CI = 1.11, 1.28 for arsenic; and PR = 1.23; 95% CI = 1.13, 1.34 for Cr[VI]), and a 0.14-unit increase in cumulative contaminant index (mean difference = 0.14; 95% CI = 0.09, 0.19; Table 3). A 10% increase in non-Latinx people of color was associated with a 21% increase in the likelihood of elevated arsenic (PR = 1.21; 95% CI = 1.07, 1.37) and a 0.10 unit increase in cumulative contaminant index (mean difference = 0.10; 95% CI = 0.01, 0.19). A 10% increase in renters was associated with a 0.07-unit increase in cumulative contaminant index (mean difference = 0.07; 95% CI = 0.01, 0.12), while the associations with other contaminants were modest. Mean cumulative contaminant index was higher in the San Joaquin Valley.

Using the detection limit rather than the MCL as the cut-off for dichotomous outcomes resulted in effect estimates for the sociodemographic variables that were slightly attenuated for arsenic, stronger for Cr(VI), and mixed for nitrate (attenuated in CWS models and stronger in DWA models; Tables E and F, available as supplements to the online version of this article at http://www.ajph.org).

DISCUSSION

To our knowledge, this is the first environmental justice analysis of drinking water quality in California communities relying on either CWSs or domestic wells. We estimated that among the nearly 39 million people in California, 1.3 million rely on domestic wells, 37.1 million rely on CWSs, and 0.5 million rely on an unknown water source. Our estimate for domestic well use is consistent with previous research suggesting that 1.2 million people use a domestic well in California,[12] and 2 to 2.5 million Californians are served by a domestic well or state small water system rather than a CWS.[13,37] The range of these estimates is a likely attributable to different data sources, time frames, and methodologies. Our study may underestimate the number of domestic well users by 240,000 to 950 000 (assuming an average household size of 3 people and a range of 1 to 4 households served per well) because we assumed that domestic wells within CWS service areas were not used.

We found that populations reliant on domestic wells faced greater water quality concerns than those served by CWSs. Mean arsenic levels exceeding

TABLE 1— Mean Water Contaminant Concentrations (2011–2019) and Sociodemographics of Domestic Well Areas (DWAs) and Community Water Systems (CWSs) Stratified by System Size: California

	DWAs[a] (n = 1914)	Small CWSs[b] (n = 1773)	Medium CWSs[c] (n = 859)	Large CWSs[d] (n = 219)
Total population, no.	1 300 193	253 098	6 030 628	30 784 197
Population (%) ≥ MCL for 1 or more contaminant	157 367 (12.1)	22 307 (8.8)	157 622 (2.6)	36 377 (0.1)
Arsenic, µg/L				
Median (IQR)	1.1 (4.3)	< DL[e]	0.6 (2.1)	0.5 (1.4)
95th percentile	14.8	9.6	6.2	3.8
Population (%) ≥ MCL[f]	106 329 (8.2)	9 187 (3.6)	20 278 (0.33)	0 (0.0)
Nitrate as N, mg/L				
Median (IQR)	1.6 (3.6)	0.8 (2.4)	0.6 (2.2)	0.7 (2.0)
95th percentile	9.7	6.4	5.3	5.1
Population (%) ≥ MCL	56 230 (4.3)	3 774 (1.5)	1 607 (0.02)	0 (0.0)
Cr(VI), µg/L				
Median (IQR)	0.3 (2.3)	< DL	< DL	0.2 (1.1)
95th percentile	9.3	8.5	6.2	4.6
Population (%) ≥ MCL	30 080 (2.3)	10 538 (4.2)	135 737 (2.2)	36 377 (0.1)
% renters	30.3	34.9	42.3	45.8
% non-Latinx White	58.2	53.5	39.7	36.7
% Latinx	30.3	34.8	45.0	38.1
% non-Latinx Black	1.8	2.7	4.0	6.1
% non-Latinx Asian	5.3	5.1	8.0	15.6
% non-Latinx Native American	1.3	1.2	0.5	0.3
% non-Latinx other	3.0	2.7	2.8	3.3
% living in poverty	32.3	37.2	38.2	33.2
% linguistically isolated	36.4	41.2	41.2	58.0

Note. Cr(VI) = hexavalent chromium; DL = detection limit; IQR = interquartile range; MCL = maximum contaminant level.

[a]DWAs represent populated portions of Census block groups.
[b]CWSs with 15–199 service connections.
[c]CWSs with 200–9 999 service connections.
[d]CWSs with ≥ 10 000 service connections.
[e]< DL indicates below the DL. DLs for individual contaminants are as follows: arsenic = 2.0 µg/L; nitrate = 0.4 mg/L; Cr(VI) = 1.0 µg/L.
[f]Population (%) ≥ MCL reflects the number and percentage of people with average water concentrations exceeding the MCL. The MCL for arsenic is 10 µg/L. The MCL for nitrate as N is 10 mg/L. Cr(VI) does not currently have an MCL; we used the most recent MCL of 10 µg/L, which was rescinded in 2017 and is in the process of being revised.

the MCL affected a greater proportion of people who use domestic wells (8.2%) compared with those who use CWSs (3.9%; Table 1). Similarly, mean nitrate and Cr(VI) levels exceeded the MCL for 4.3% and 2.3% of the population in DWAs compared with 0.01% and 0.49% of the population served by CWSs, respectively. Although Bangia et al. did not incorporate domestic well locations into their analysis, their study on individual concentrations and MCL violations for 12 contaminants including arsenic, nitrate, and Cr(VI) similarly concluded that cumulative contaminant burdens were higher in areas outside CWSs.[37] Our finding of an association between small system size and elevated nitrate and arsenic concentrations is consistent with previous CWS studies in the San Joaquin Valley[6,9] and statewide.[37] Bangia et al. found that the most frequent MCL violations occur in small CWSs and the highest cumulative contaminant concentrations occur in the San Joaquin Valley.[37]

Previous empirical work suggests that natural, built, sociopolitical, and environmental factors mediate the actions of state, county, community,

TABLE 2— Generalized Additive Model Results Estimating the Association Between Sociodemographic Variables and 2011–2019 Mean Drinking Water Contaminant Concentrations Among Community Water Systems (CWSs): California

Dependent Variables	Arsenic ≥ 1/2 MCL (n = 2723), PR[a] (95%CI)	Nitrate ≥ 1/2 MCL (n = 2744), PR (95% CI)	Cr(VI) ≥ 1/2 MCL (n = 2628), PR (95% CI)	Cumulative Contaminant Index[b] (n = 2617), B[c] (95% CI)
% Latinx[d]	1.14 (1.06, 1.22)	1.21 (1.12, 1.30)	1.31 (1.21, 1.43)	0.11 (0.08, 0.14)
% non-Latinx people of color[d]	0.97 (0.85, 1.10)	1.31 (1.15, 1.49)	1.28 (1.12, 1.46)	0.07 (0.02, 0.12)
% renter[d]	0.94 (0.86, 1.02)	1.00 (0.91, 1.10)	0.97 (0.88, 1.06)	0.00 (–0.03, 0.03)
Groundwater source	9.31 (4.81, 18.05)	7.32 (3.71, 14.43)	4.77 (2.64, 8.52)	0.64 (0.51, 0.77)
15–199 service connections[e]	1.24 (0.92, 1.68)	1.43 (1.01, 2.03)	1.29 (0.91, 1.84)	0.15 (0.02, 0.27)
Central Coast[f]	1.30 (0.56, 3.02)	0.73 (0.32, 1.65)	. . .[g]	0.74 (0.38, 1.09)
Eastern Sierra	0.34 (0.12, 0.99)	. . .[h]	. . .[g]	0.31 (–0.11, 0.72)
Imperial Valley and Mojave Desert	0.23 (0.04, 1.15)	0.46 (0.11, 1.89)	. . .[g]	0.00 (–0.60, 0.60)
Northern California	2.28 (0.73, 7.12)	0.97 (0.31, 3.03)	. . .[g]	0.28 (–0.16. 0.72)
Northern Sierra	2.10 (0.90, 4.92)	0.56 (0.18, 1.78)	. . .[g]	0.65 (0.27, 1.04)
San Joaquin Valley	1.36 (0.66, 2.28)	1.26 (0.51, 3.12)	. . .[g]	1.10 (0.78, 1.42)
Southern California	0.61 (0.19, 1.93)	0.31 (0.10, 0.97)	. . .[g]	0.49 (0.01, 0.98)
AIC	1 676.65	1 294.82	1 253.61	9 006.18
Log likelihood	−809.73 (*df* = 28.60)	−625.4 (*df* = 22.00)	−604.07 (*df* = 22.74)	−4473.06 (*df* = 30.0)
Moran's I *P*	.78	.67	.8	.99

Note. AIC = Akaike information criterion; CI = confidence interval; MCL = maximum contaminant level. The California MCL for arsenic is 10 μg/L. The MCL for nitrate as N is 10 mg/L. Cr(VI) does not currently have an MCL; we used the most recent MCL of 10 μg/L, which was rescinded in 2017 and is in the process of being revised.

[a]PRs are prevalence ratios obtained by exponentiating the binomial model regression coefficients.
[b]The cumulative contaminant index (CCI) is the sum of individual mean contaminant concentrations (arsenic, nitrate, and Cr[VI]) divided by half of their respective MCLs. CCI ranged from 0.00 to 25.6 with a mean of 1.0 across all CWSs in the state.
[c]Estimates represent a mean difference and were obtained from Gaussian model parameter estimates.
[d]Continuous dependent variables were scaled by 10%.
[e]Comparison group is medium or large CWSs (≥ 200 service connections).
[f]Comparison group is the San Francisco Bay Area region.
[g]Region excluded from this model because Cr(VI) is a more localized contaminant than arsenic or nitrate.
[h]No CWSs in this region had the outcome.

and household actors in ways that result in drinking water disparities across race and class.[7] Consistent with this, water quality outcomes were significantly associated with race and ethnicity among both DWAs and CWSs in our analysis. Balazs et al. similarly found that, in the San Joaquin Valley, CWSs serving larger percentages of Latinx populations receive drinking water with higher nitrate levels, with a stronger association among small water systems (15–199 connections) than larger systems.[9] In addition, Balazs et al. reported that higher home ownership rates were associated with lower arsenic in the San Joaquin Valley.[6] In our analysis, we did not find associations between tenancy and arsenic concentrations in CWSs. However, we found a significant positive association between arsenic concentration and the proportion of Latinx residents in DWAs. Our results align with national county-level analyses showing greater arsenic MCL exceedances in CWSs reliant on groundwater, serving smaller populations, and serving Latinx populations,[43] and domestic wells in semi-urban Latinx communities.[44]

Our study expands upon previous research by considering multiple chemical contaminants, deriving a cumulative contaminant index, and incorporating domestic well populations through dasymetric mapping to produce refined population and sociodemographic estimates for both DWAs and CWSs.

Limitations of our study include the omission of state small water systems,

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TABLE 3— Generalized Additive Model Results Estimating the Association Between Sociodemographic Variables and 2011–2019 Mean Groundwater Contaminant Levels Among Domestic Well Areas: California

Dependent Variables	Arsenic ≥ 1/2 MCL (n = 1782), PR[a] (95% CI)	Nitrate ≥ 1/2 MCL (n = 1917), PR (95% CI)	Cr(VI) ≥ 1/2 MCL (n = 1597), PR (95% CI)	Cumulative Contaminant Index[b] (n = 1587), B[c] (95% CI)
% Latinx[d]	1.13 (1.05, 1.21)	1.19 (1.11, 1.28)	1.23 (1.13, 1.34)	0.14 (0.09, 0.19)
% non-Latinx people of color[d]	1.21 (1.07, 1.37)	1.07 (0.93, 1.24)	1.11 (0.94, 1.30)	0.10 (0.01, 0.19)
% renter[d]	1.07 (0.99, 1.16)	1.06 (0.98, 1.16)	1.06 (0.95, 1.17)	0.07 (0.01, 0.12)
Central Coast[e]	0.96 (0.37, 2.48)	0.82 (0.35, 1.91)	. . .[f]	0.22 (−0.42, 0.86)
Eastern Sierra	0.83 (0.31, 2.25)	0.14 (0.01, 1.40)	. . .[f]	0.10 (−0.60, 0.80)
Imperial Valley and Mojave Desert	2.48 (0.34, 18.16)	1.13 (0.15, 8.56)	. . .[f]	0.04 (−1.21, 1.28)
Northern California	0.51 (0.18, 1.50)	0.41 (0.07, 2.28)	. . .[f]	−0.37 (−1.14, 0.40)
Northern Sierra	1.30 (0.56, 3.00)	1.11 (0.33, 3.77)	. . .[f]	0.41 (−0.22, 1.04)
San Joaquin Valley	1.91 (0.91, 3.99)	1.31 (0.55, 3.12)	. . .[f]	0.90 (0.37, 1.44)
Southern California	2.58 (0.61, 10.96)	0.17 (0.04, 0.30)	. . .[f]	0.04 (−0.90, 0.97)
AIC	1 700.72	1 466.24	1 028.27	6 339.41
Log-likelihood	−821.32 (*df* = 29.05)	−702.40 (*df* = 30.72)	−492.48 (*df* = 21.66)	−3140.16 (*df* = 29.55)
Moran's I *P*	.82	.63	.96	.54

Note. AIC = Akaike information criterion; CI = confidence interval; MCL = maximum contaminant level. The California MCL for arsenic is 10 µg/L. The MCL for nitrate as N is 10 mg/L. Cr(VI) does not currently have an MCL; we used the most recent MCL of 10 µg/L, which was rescinded in 2017 and is in the process of being revised.

[a]PRs are prevalence ratios obtained by exponentiating the binomial model regression coefficients.
[b]The cumulative contaminant index (CCI) is the sum of individual mean contaminant concentrations (arsenic, nitrate, and Cr[VI]) divided by half of their respective MCLs. CCI ranged from 0.0 to 112.6 with a mean of 1.8 across all DWAs in the state.
[c]Estimates represent a mean difference obtained from Gaussian model regression coefficients.
[d]Continuous dependent variables were scaled by 10%.
[e]Comparison group is the San Francisco Bay Area region.
[f]Region excluded from this model because Cr(VI) is a more localized contaminant than arsenic or nitrate.

which may have resulted in misclassifying domestic well areas that were actually state small systems. Because well completion reports had no information about current well use, our analysis may have overestimated the domestic well population by including inactive wells. The water quality data we used is a first-order approximation of household contaminant concentrations and assumes untreated groundwater samples are an accurate proxy for DWAs' water quality. Missing data contribute to uncertainty in our analysis and may have led to underestimates of contaminant concentrations, particularly in smaller CWSs (which are more likely than larger systems to violate monitoring requirements)[45] and in DWAs, where monitoring is not required. This may have led us to overestimate disparities across CWSs, as smaller systems have lower proportions of people of color and renters, and higher water-quality concerns (Table 1).

Our analysis may also have underestimated nitrate concentrations in DWAs because domestic wells tend to draw from shallow aquifers, while we relied on averaged samples from both shallow and deep aquifers. By contrast, Ransom et al.[46] modeled nitrates in shallow aquifers (< 500 meters) of California's Central Valley and considered depth to groundwater as a predictor, and the Groundwater Ambient Monitoring and Assessment program considered depth to groundwater in estimating water quality in their domestic well water study.[47] Future work is needed to improve contaminant concentration estimates at various aquifer depths for a broader set of chemicals.

Finally, we were not able to assess the extent to which our population relies on tap water for drinking as opposed to other sources, such as bottled water. National survey data indicate that Black and Latinx populations are less likely to consume tap water than Whites, which could attenuate the racial disparities in exposure to tap water contaminants suggested by our analysis. However, people may still be exposed to tap water contaminants through cooking and bathing. Additional research is also needed on the mechanisms through which the inequalities we observed are produced and can be remedied, as well as the unique vulnerabilities of unincorporated communities and unhoused individuals.

Our results suggest that a substantial number of Californians rely on domestic wells in areas of poor groundwater quality and that communities of color statewide are disproportionately affected by arsenic, nitrate, and Cr(VI) contamination of drinking water, both in CWSs and DWAs, with findings most pronounced in DWAs. Our study provides further evidence of unequal access to safe drinking water in California and, through our identification of DWAs, can support decision-makers in their efforts to (1) identify regions where more frequent water quality testing is needed to characterize the threats in domestic well communities; (2) elucidate solutions, including consolidation opportunities between DWAs with poor water quality and nearby CWSs with good water quality; and (3) safeguard drinking water supplies, prioritize funding, and track progress toward the human right to water. AJPH

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CONTRIBUTORS

C. Pace participated in data curation, formal analysis, methodology, visualization, and writing the original draft. C. Balazs and L. J. Cushing participated in conceptualization, funding acquisition, methodology, and writing, reviewing, and editing. K. Bangia and N. Depsky participated in data curation and methodology. A. Renteria participated in funding acquisition, methodology, and visualization. R. Morello-Frosch participated in conceptualization, funding acquisition, methodology, supervision, and writing, reviewing, and editing.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

HUMAN PARTICIPATION PROTECTION

This study was exempt from institutional board review because no human participants were involved.

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