Race, Racism, and Drinking Water Contamination Risk From Oil and Gas Wells in Los Angeles County, 2020

Alique G. Berberian, MPH, MIA, Jenny Rempel, MA, Nicholas Depsky, MS, Komal Bangia, MPH, Sophia Wang, and Lara J. Cushing, PhD, MPH

See also Oil and Gas: Environmental Justice, pp. 1173–1200.

Objectives. To evaluate the potential for drinking water contamination in Los Angeles (LA) County, California, based on the proximity of supply wells to oil and gas wells, and characterize risk with respect to race/ethnicity and measures of structural racism.

Methods. We identified at-risk community water systems (CWSs) as those with supply wells within 1 kilometer of an oil or gas well. We characterized sociodemographics of the populations served by each CWS by using the 2013–2017 American Community Survey. We estimated the degree of redlining in each CWS service area by using 1930s Home Owners' Loan Corporation security maps, and characterized segregation by using the Index of Concentration at the Extremes. Multivariable regression models estimated associations between these variables and CWS contamination risk.

Results. A quarter of LA County CWSs serving more than 7 million residents have supply wells within 1 kilometer of an oil or gas well. Higher percentages of Hispanic, Black, and Asian/Pacific Islander residents and a greater degree of redlining and residential segregation were associated with higher contamination risk.

Conclusions. Redlining and segregation predict drinking water contamination risks from oil development in LA County, with people of color at greater risk. (*Am J Public Health*. 2023;113(11):1191–1200. https://doi.org/10.2105/AJPH.2023.307374)

AJPH November 2023, Vol 113, No. 11

Oil production in the United States has nearly doubled over the past decade,[1] with more than 17 million people now living within 1 mile of an active oil or gas well.[2] Studies have found evidence of groundwater contamination near oil and gas development from volatile organic compounds (e.g., benzene, toluene, ethylbenzene, and xylenes), trace elements (e.g., arsenic, lead), and other organic compounds (e.g., methane), some of which are known endocrine disruptors, carcinogens, neurotoxins, or developmental toxins.[3–5] Groundwater contamination can result from well and wellbore failures, deterioration, and poor maintenance, or via contamination pathways formed during well stimulation (e.g., acidization, hydraulic fracturing or "fracking"). Idle wells can be conduits for contaminants from active wells to migrate to underground drinking water sources,[6] and deteriorating cement and steel casings in high-pressure storage wells can cause leaks.[7]

Fossil fuel development in California is concentrated in neighborhoods with higher proportions of people of color and lower socioeconomic status.[8,9] Historical redlining has also been associated with the present-day distribution of oil and gas wells.[10] Nationwide, neighborhoods that received the poorest investment risk grade in redlining maps published by the federal Home Owners' Loan Corporation (HOLC) in the 1930s have nearly twice the density of oil and gas wells as neighborhoods that received the best grade.[10]

The unusual proximity of oil and gas wells to a population of 10 million people makes Los Angeles (LA) County, California, an important setting for examining drinking water contamination risks from oil and gas development. LA County has more than 20 000 active and inactive oil and gas wells and produces almost 14 million barrels of oil annually.[11] Approximately 500 000 residents live within half a mile of an active well.[12] LA County is also unique with respect to its number of drinking water providers. While most major US metropolitan areas are served by a few providers, LA County residents are served by approximately 200 community water systems (CWSs)—systems that serve at least 25 year-round residents or have at least 15 service connections. CWSs serve drinking water that may come from a single or variety of groundwater wells, surface water, and purchased water sources that are often blended before distribution. Nearly 30% of the county's total water supply is sourced from groundwater, and almost half of its CWSs rely entirely on groundwater.[13]

We sought to determine how racism in the housing market relates to the risk of drinking water contamination from oil and gas development in LA County. We used information about the location of oil and gas and groundwater supply wells to estimate the potential for contamination based on proximity. We then examined whether the racial/ethnic makeup, degree of historical redlining, and present-day racial residential segregation of a CWS's service area were associated with the likelihood that 1 or more of its supply wells are located near an oil or gas well. We examined race/ethnicity to describe disparities in risk and considered redlining and segregation as measures of structural racism in the housing market that may have contributed to present-day racialized disparities.[14]

METHODS

We considered all CWSs in LA County, with systems as the unit of analysis. We first combined data on the location of (1) oil and gas wells from the California Department of Conservation Geologic Energy Management Division (CalGEM) and (2) drinking water supply wells from the California State Water Resources Control Board to define CWSs at risk for oil and gas–related contamination based on spatial proximity of supply wells to oil or gas wells. We then used CWS service area boundaries from the Tracking California Drinking Water Systems Geographic Reporting Tool and data from the American Community Survey (ACS) to characterize the sociodemographic characteristics and degree of residential segregation of the population served by each CWS. Redlining measures were derived by overlaying CWS service area boundaries with 1930s HOLC investment risk maps. We used multivariable regression models to test the associations between race/ethnicity, redlining, and segregation and drinking water contamination risk.

Oil and Gas Wells

We downloaded oil and gas well coordinates, status (e.g., active, idle), and type (e.g., oil and gas, storage, injection) from the CalGEM database of permits on July 18, 2021.[15] Because it is unclear how frequently well status is updated in the CalGEM database, we used monthly production data from the California Department of Conservation to identify active versus inactive or idle extraction wells.[11] Extraction wells were considered active if any oil or gas production was reported from 2018 to 2020 and inactive if no production was reported or production data were missing during this period, resulting in a change in status for about 3% of production wells relative to their CalGEM designation. We then grouped oil and gas wells based on type and production status: active extraction wells ($n = 2700$), inactive extraction wells ($n = 16\,616$), and storage and disposal wells ($n = 804$). We excluded offshore facilities and canceled wells (i.e., permit canceled before drilling; Figure A, available as a supplement to the online version of this article at https://ajph.org).

Drinking Water Supply Wells

We obtained coordinates and unique CWS identifiers for active public drinking water supply wells ($n = 1064$) from the Division of Drinking Water at the California State Water Resources Control Board. We restricted our analysis to wells that supply groundwater to CWSs in LA County with complete location information, leaving a final subset of 901 wells (Figure A).

Supply wells were considered at risk of potential contamination if they were located within 1 kilometer of at least 1 active extraction, inactive extraction, storage, or disposal well (Figure B, available as a supplement to the online version of this article at https://ajph.org). We selected this 1-kilometer buffer in accordance with a state law banning new oil and gas development within 3200 feet (~1 km) of homes, schools, and health care facilities. We also conducted a sensitivity analysis using a 2-kilometer buffer.

Community Water Systems

We obtained service area boundaries for 196 CWSs that directly served residential populations (i.e., excluding wholesale systems) and were listed as "active" in California's Safe Drinking Water Information System as of 2018 from the Tracking California Drinking

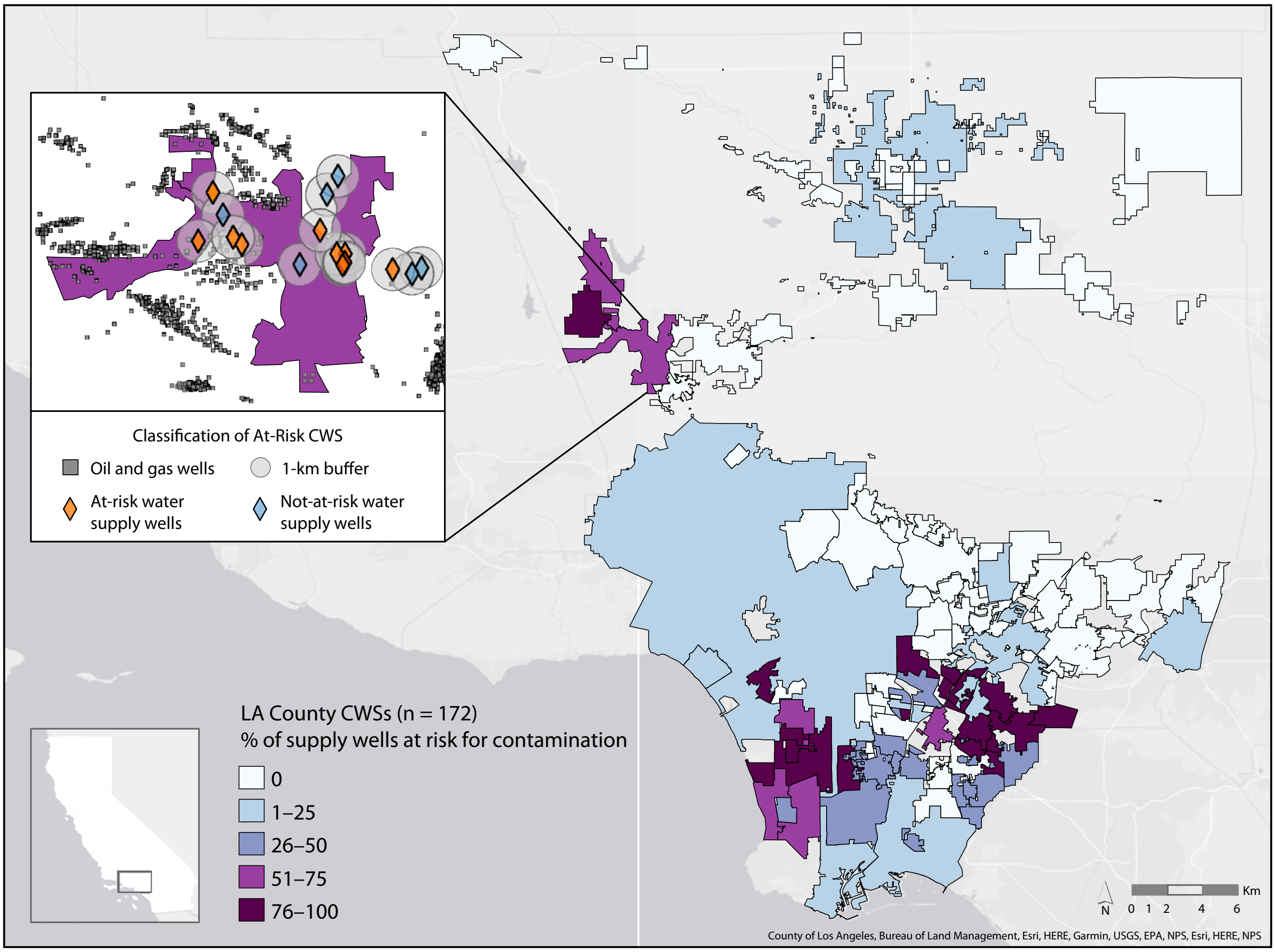

FIGURE 1— **Percentage of Drinking Water Supply Wells at Risk for Oil and Gas Contamination per Community Water System (CWS): Los Angeles County, CA, 2020**

Note. A CWS was considered at risk if 1 or more of its drinking water supply wells was within 1 km of an oil or gas well. At-risk systems are shaded, whereas ones not at risk are white.

Water Systems Geographic Reporting Tool.[16,17] We obtained system size (number of service connections) from the Division of Drinking Water's Electronic Data Transfer Library, and we obtained data on systems' primary water source from California's Safe Drinking Water Information System. We excluded CWSs that served incarcerated populations for which facility-specific sociodemographic data were unavailable (n = 2), relied exclusively on surface or purchased water (n = 21), or were located on the Channel Islands (n = 1), leaving 172 CWSs. We resolved service area boundary overlaps by following the approach used by Pace et al.[18] We calculated the fraction of at-risk supply wells for each CWS, and we classified those with at least 1 supply well within the 1-kilometer buffer area of any oil or gas well as at-risk (Figure 1).

Sociodemographic Characteristics

We characterized the population served by each CWS by using block group–level sociodemographic estimates from the 2013–2017 5-year ACS downscaled via dasymetric mapping, following the approach described in Pace et al.[18] For each CWS, we calculated the percentage of residents identifying as Hispanic/Latino, non-Hispanic White, non-Hispanic Black, non-Hispanic Asian/Pacific Islander, non-Hispanic Native American, and non-Hispanic other races (including multiracial), as well as the proportion of renters and population with income below twice the federal poverty level as determined by the US Census. Household metrics included median annual household income and the percentage of linguistically isolated households (where no one aged older than 14 years speaks English "very well").

Redlining Measures

Redlining measures were assigned using digitized 1939 HOLC-graded neighborhood boundaries obtained from the Mapping Inequality Project (n = 416 HOLC neighborhood polygons).[19] Because HOLC neighborhood boundaries did not overlap perfectly with CWS service area boundaries, we used areal apportionment to assign redlining measures. We first calculated the area of the CWS that overlapped any HOLC polygon to find the percentage area that was graded versus ungraded. For CWSs whose service areas overlapped with HOLC polygons (n = 85), we calculated the percentage of the graded area within the CWS that was graded A ("best"), B ("still desirable"), C ("definitely declining"), or D ("hazardous"; i.e., redlined). We additionally constructed a weighted redlining score ranging from 0 to 100 by weighting each graded portion of the CWS as follows:

$$\frac{\sum (p_i \times w_i)}{\sum p_i} \tag{1}$$

where p is the percentage of the CWS area given grade i, and w is the weight, with grade A weight = 25; B = 50; C = 75; and D = 100. For example, if a CWS boundary was intersected by 2 HOLC polygons such that 30% of its area overlapped with a "B"-graded HOLC polygon, 50% with a "C"-graded polygon, and 20% was not covered by HOLC polygons (i.e., ungraded), the score would be $[(30 \times 50) + (50 \times 75)]/(30 + 50) = 66$. Weighted redlining scores closer to 100 indicate that a greater proportion of the CWS's service area received poorer HOLC grades.

Segregation Metrics

We used 2013–2017 ACS data to compute the Index of Concentration at the Extremes (ICE), an area-based measure of concentrated racialized economic segregation, based on household income and race/ethnicity by census tract,[20] following the method described in Krieger et al.[21] We assigned census tracts to CWSs if their centroid intersected with CWS boundaries. For CWSs that did not intersect with any centroids, we assigned them the tracts with which they overlapped.

ICE ranges from −1 to 1, with the lowest values indicating the highest concentration of marginalized populations—which we defined as people of color in households earning less than $25 000 per year—and values closer to 1 indicating higher concentrations of privilege—which we defined as non-Hispanic White people in households earning more than $100 000 per year. We then categorized this measure by quartiles, with Q1 representing the most marginalized and Q4 the most privileged. We also calculated a weighted ICE score ranging from 0 to 100 using a formula analogous to the weighted redlining score, where p is the percentage of tracts in each CWS in quartile i, and w is the weight, with Q4 weight = 25; Q3 = 50; Q2 = 75; and Q1 = 100. The numerator was divided by 100.

Statistical Analysis

We calculated descriptive statistics and correlation coefficients to examine the distribution and bivariate associations between all variables of interest. We then used multivariable regression to estimate associations between the race/ethnicity, redlining, and ICE variables, and 2 outcomes: (1) at-risk status (yes or no, Poisson with robust standard errors) and (2) the percentage of CWS supply wells at risk (linear, ordinary least-squares with robust standard errors). We estimated prevalence ratios (PRs) by using a modified Poisson model rather than odds ratios because the outcome was not rare and to increase the interpretability of the effect estimates.[22] We used robust standard errors with a "sandwich" estimator because Poisson regression overestimates error for relative risk measures and to help address likely issues with spatial autocorrelation attributable to the clustering of oil and gas wells.[23] Poisson models estimating associations with the binary outcome included all CWSs in our sample (n = 172). We restricted linear models estimating associations with the continuous outcome to at-risk CWSs (n = 47 systems with at least 1 at-risk drinking water supply well). We scaled continuous predictor variables in all 5 models to facilitate comparison of model coefficients by subtracting the mean from each variable and dividing by the standard deviation (SD). We exponentiated coefficients from the Poisson models to obtain PRs.

We assessed unadjusted associations between our outcomes and CWS racial/ethnic makeup in models including the following variables, with percentage non-Hispanic White as the reference group: percentage Hispanic, percentage non-Hispanic Black, percentage non-Hispanic Asian/Pacific Islander, percentage non-Hispanic Native American, and percentage non-Hispanic other race including multiracial. Non-Hispanic Asian and Pacific

Islander were collapsed despite the considerable diversity across and within these groups because of limitations of sample size. Adjusted models additionally controlled for CWS size as a precision variable (< 10 000 service connections [small or medium] vs ≥ 10 000 [large]), and measures of socioeconomic status chosen a priori: housing tenure (% renters), linguistic isolation, and poverty. In the case of the linear model estimating the association between racial/ethnic makeup and the proportion of CWS supply wells at risk, we omitted percentage of linguistic isolation because of multicollinearity. We omitted median household income from both sets of models given collinearity with poverty.

We assessed unadjusted associations between our outcomes and CWS redlining in separate models that considered percentage graded C or D or the weighted redlining score as the exposure metric. We combined the 2 least-desirable grades of C and D because of multicollinearity. Adjusted redlining models considering percentage graded C or D additionally controlled for percentage graded B (with percentage graded A as the reference group), percentage ungraded, and CWS size. Adjusted redlining models considering the weighted redlining score additionally controlled for percentage ungraded and CWS size. Percentage ungraded was included in both models as a precision variable.

We assessed unadjusted associations between our outcomes and ICE in separate models that considered the percentage ICE Q1 (most marginalized) or the weighted ICE score. Adjusted models with percentage ICE Q1 additionally controlled for percentage ICE in Q2 and Q3 (with ICE Q4 as the reference group) and system size as a precision variable. Adjusted models with the weighted ICE score additionally controlled for system size.

RESULTS

The final sample included 172 CWSs and 901 groundwater supply wells across LA County. We estimated that 47 medium and large (i.e., > 200 service connections) CWSs were at risk for oil and gas–related contamination, leaving 125 CWSs not at risk (Table 1). At-risk CWSs had higher average proportions of people of color, renters, linguistically isolated households, poverty rates, and lower median household income compared with CWSs not at risk (Table 1). On average, at-risk CWSs had a lower proportion of their service area graded “A” (“desirable”), a higher proportion graded “D” (“hazardous”), and a higher mean weighted redlining score compared with CWSs not at risk. Similarly, when compared with not-at-risk systems, at-risk systems had a higher proportion of their census tracts in ICE Q1 (marginalized) and a higher mean weighted ICE score. Among at-risk CWSs, almost one third had more than three quarters of their supply wells located within 1 kilometer of an oil or gas well (Figure 1, Figure B).

Sociodemographic variables were moderately correlated with redlining variables (Pearson’s correlation coefficients [ρ] between −0.39 and 0.38) and strongly correlated with ICE variables (ρ between −0.85 and 0.81). Redlining and ICE variables were weakly correlated (ρ between −0.30 and 0.29), and the percentage of at-risk supply wells was weakly correlated with sociodemographic, redlining, and ICE variables (ρ between −0.27 and 0.30; Figure C, available as a supplement to the online version of this article at https://ajph.org).

Unadjusted and adjusted Poisson models suggested that higher percentages of Hispanic, non-Hispanic Black, and non-Hispanic Asian/Pacific Islander residents were associated with a higher likelihood of being served by an at-risk CWS (Figure 2; Table A, available as a supplement to the online version of this article at https://ajph.org). A 1-unit-SD increase in percentage Hispanic, percentage non-Hispanic Black, and percentage non-Hispanic Asian/Pacific Islander was associated with a 181%, 33%, and 24% higher likelihood of being served by an at-risk system in adjusted models, respectively, holding other variables constant (percentage Hispanic: PR = 2.81; 95% confidence interval [CI] = 1.84, 4.30; percentage non-Hispanic Black: PR = 1.33; 95% CI = 1.10, 1.61; and percentage non-Hispanic Asian/Pacific Islander: PR = 1.24; 95% CI = 0.87, 1.78).

Redlining and racialized economic marginalization were associated with a higher likelihood of being served by an at-risk CWS in unadjusted and adjusted Poisson models (Figure 3; Tables B and C, available as supplements to the online version of this article at https://ajph.org). A 1-unit-SD increase in percentage graded C or D was associated with a 126% higher likelihood of being served by an at-risk system, controlling for percentage graded B, percentage ungraded, and system size (PR = 2.26; 95% CI = 1.13, 4.50). A 1-unit-SD increase in weighted redlining score was associated with a 27% higher likelihood of being served by an at-risk system, holding percentage ungraded and system size constant (PR = 1.27; 95% CI = 1.03, 1.56). A 1-unit-SD increase in percentage of CWS census tracts in Q1 of ICE was associated with 49% higher likelihood of being served by an at-risk system, controlling for

TABLE 1— Characteristics of At-Risk and Not-At-Risk Community Water Systems Based on Drinking Water Supply Well Proximity to Oil and Gas Wells: Los Angeles County, CA, 2020

	At-Risk CWS (n = 47)	Not-at-Risk CWS (n = 125)
Total population served, no.	7 180 196	2 204 316
CWS size, no.		
Small (< 200 connections)	0	47
Medium (200–9999 connections)	24	61
Large (≥ 10 000 connections)	23	17
Sociodemographics, mean %		
Hispanic	59.8	40.2
Non-Hispanic White	19.3	39.2
Non-Hispanic Asian/Pacific Islander	11.0	10.9
Non-Hispanic Black	7.5	6.5
Non-Hispanic other race including multiracial	2.0	2.8
Non-Hispanic Native American	0.2	0.3
Linguistically isolated	13.4	9.4
Renters	48.8	35.5
Poverty[a]	37.9	36.0
Median household income, mean $	66 214	66 810
HOLC redlining grade,[b] mean %		
A	2.6	9.1
B	13.6	17.6
C	55.8	55.4
D	28.0	17.9
Ungraded	65.8	52.2
Weighted redlining score (0–100),[c] mean	77.3	70.5
ICE quartile[d], mean %		
1	29.5	11.5
2	29.9	21.0
3	19.8	32.8
4	19.7	34.0
Weighted ICE score (0–100),[e] mean	66.8	52.2
Amount of supply wells within 1 km of an oil or gas well, no. (%)		
Low (≤ 25%)	10 (21)	0
Medium (26%–50%)	16 (34)	0
High (51%–75%)	6 (13)	0
Very high (76%–100%)	15 (32)	0
Primary water source, no. (%)		
Groundwater	14 (29.8)	76 (60.8)
Surface water	33 (70.2)	49 (39.2)

Note. CWS = community water system; HOLC = Home Owners' Loan Corporation; ICE = Index of Concentration at the Extremes. Descriptive statistics are provided for at-risk and not-at-risk CWSs based on their service area. An at-risk CWS was defined as having at least 1 water supply well within 1 km of an active, inactive, or storage or disposal well. Eleven systems had at least 1 supply well within 1 km of an active oil or gas well.

[a] Poverty was defined as below twice the federal poverty level based on the US Census.

[b] Only 85 out of 172 CWSs intersected with neighborhoods assigned a grade of A ("best"), B ("still desirable"), C ("definitely declining"), or D ("hazardous"; i.e., redlined) for investment by HOLC.

[c] Weighted redlining scores closer to 100 indicate that a greater proportion of the CWS's HOLC-graded area received lower HOLC grades (e.g., more D-graded areas).

[d] We categorized ICE (–1 to 1) into quartiles, with Q1 representing the highest concentration of racialized economic marginalization and Q4 the highest concentration of racialized economic privilege.

[e] Weighted ICE scores closer to 100 indicate that a greater proportion of the CWS's census tracts are marginalized.

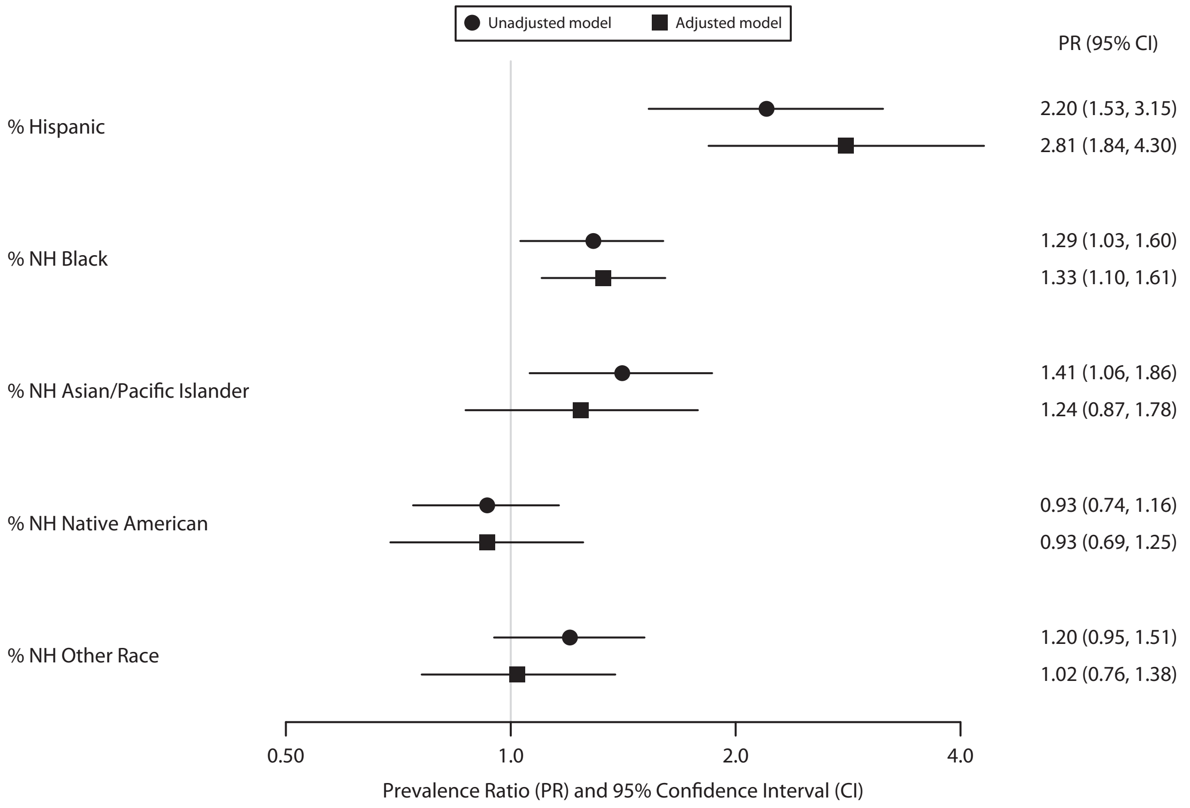

FIGURE 2— **Likelihood of Being Served by an At-Risk Community Water System (CWS) Associated With Racial/Ethnic Make-Up: Los Angeles County, CA, 2020**

Note. NH = non-Hispanic. The sample size was n = 172. The adjusted model for race/ethnicity (model 1) controlled for CWS size, percentage linguistically isolated, percentage renters, and percentage poverty. Explanatory variables have been scaled in units of SD.

percentage ICE Q2, percentage ICE Q3, and system size (PR = 1.49; 95% CI = 1.18, 1.88). A 1-unit-SD increase in weighted ICE score was associated with 62% higher likelihood of being served by an at-risk system, controlling for system size (PR = 1.62; 95% CI = 1.24, 2.13).

Linear models similarly suggested that among at-risk systems, higher percentages of Hispanic and non-Hispanic Black residents were associated with a greater percentage of at-risk drinking water supply wells, particularly when controlling for socioeconomic variables, although estimates were less precise (Table D, available as a supplement to the online version of this article at https://ajph.org). A 1-unit-SD increase in percentage Hispanic and percentage non-Hispanic Black was associated with a 38% and 8% increase, respectively, in the percentage of at-risk supply wells per CWS (percentage Hispanic: mean difference = 38.47; 95% CI = 9.90, 67.03; percentage non-Hispanic Black: mean difference = 7.62; 95% CI = –0.57, 15.81). Redlining was also weakly associated with an increase in percentage of at-risk supply wells, while ICE Q1 was associated with a slight decrease; however, in both cases, CIs were wide and crossed the null (Tables E and F, available as supplements to the online version of this article at https://ajph.org).

Effect estimates were consistent in direction in our sensitivity analysis using a 2-kilometer buffer distance to define at-risk drinking water supply wells (Tables A–F).

DISCUSSION

We found that almost a quarter of LA County CWSs serving more than 7 million residents have drinking water supply wells located within 1 kilometer of an oil or gas well, increasing the possibility of contamination. Five systems serving more than 162 000 residents source their water entirely from at-risk groundwater wells; one of these systems serves the Pitchess Detention Facility and was excluded from our analysis because sociodemographic data were unavailable. Seven additional systems serving more than 189 000

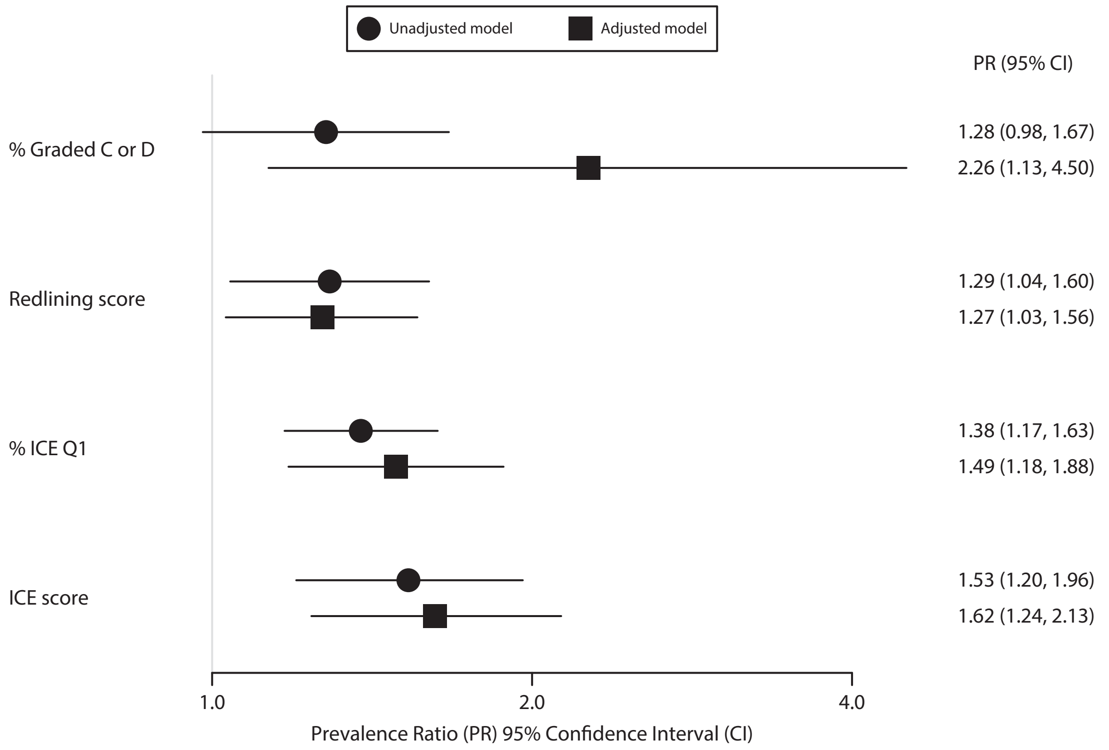

FIGURE 3— **Likelihood of Being Served by an At-Risk Community Water System Associated With Historical Redlining (HOLC Grade) and Segregation (ICE): Los Angeles County, CA, 2020**

Note. HOLC = Home Owners' Loan Corporation; ICE = Index of Concentration at the Extremes. The adjusted model for percentage graded C or D (model 2; n = 85) controlled for percentage graded B, percentage ungraded, and CWS size. The adjusted model for redlining score (model 3; n = 85) controlled for percentage ungraded and CWS size. The adjusted model for percentage ICE Q1 (model 4; n = 172) controlled for percentage ICE Q2, percentage ICE Q3, and CWS size. The adjusted model for ICE score (model 5; n = 172) controlled for CWS size. Explanatory variables have been scaled in units of SD.

residents also source their groundwater entirely from at-risk supply wells but additionally purchase surface water, making their water supply less vulnerable to possible oil and gas development–related groundwater contamination.

Several studies document associations between oil and gas development and elevated drinking water contamination risk in regions where fracking is common. A Wyoming study identified well-stimulation chemicals like naphthalene in groundwater and benzene, toluene, ethylbenzene, and xylenes in a drinking water well in an area of oil and gas production.[4] A study of more than a dozen US states found that almost half of all fracking wells stimulated in 2014 were located within 2 to 3 kilometers of at least 1 domestic groundwater well.[24] In the LA Basin, fracking has been used in close vertical proximity to protected aquifers.[25] Acidization using hydrochloric and hydrofluoric acids, methanol, naphthalene, ethylbenzene, and xylene is a more frequently used well-stimulative technique in LA County and can contaminate groundwater through improper wastewater management or disposal (e.g., injection into protected aquifers).[26] Many chemicals used in oil and gas development are not currently regulated in drinking water, including per- and polyfluoroalkyl substances, which means little monitoring data exist to assess potential impacts.

Racial/ethnic composition, residential segregation, and historical redlining were significant predictors of drinking water contamination risks from oil and gas development in LA County in our study. CWSs with higher proportions of Hispanic, non-Hispanic Black, and non-Hispanic Asian/Pacific Islander residents, a higher proportion of their service area redlined in the 1930s, and a higher degree of present-day racialized economic segregation were all more likely to have oil or gas wells within 1 kilometer of their drinking water supply wells. Although we did not perform a formal mediation analysis, this suggests racism in the housing market contributed to present-day racial disparities in oil and gas contamination risk. Our analysis adds to a growing body of literature on the likely disproportionate impact of oil and gas development on communities of color[27,28] and the influence of past redlining on contemporary residential proximity to environmental hazards.[29]

Interestingly, in models assessing the influence of racial/ethnic composition on drinking water contamination risk, higher CWS poverty levels were associated with a reduced risk. This is in contrast with an Ohio study that found lower-income block groups were associated with the presence of oil and gas wastewater injection wells[30] and a study in Southern Texas that found disproportionate siting of disposal wells in high-poverty block groups.[31] Our contrasting findings may relate to the fact that our study area included suburban and urban areas with wide variation in the cost of living that was not factored into our measure of poverty.

Within at-risk systems, we also found that higher concentrations of marginalized populations (ICE Q1) were associated with a reduced proportion of at-risk supply wells, counter to our hypothesis. This suggests that segregation is more reflective of the likelihood of contamination risk but not necessarily the severity.

We were limited by a small sample size of at-risk CWSs in our linear models ($n = 47$), which reduced the precision of our results. Because of limited data, we were not able to account for the extent, chemistry, and depth of drinking water aquifers, or the age, depth, or condition of oil and gas wells. We were also not able to consider blending of different water sources by CWSs before drinking water distribution. Our outcome measure of an at-risk CWS should therefore be interpreted as an indication of potential contamination risk and not a measure of exposure.

Some of the oil and gas wells in our analysis were likely drilled before the creation of LA County redlining maps in the late 1930s; therefore, part of the associations we observed between historical redlining and drinking water contamination risk may be the result of differences in the distribution of oil and gas wells that predated the maps. The presence of nearby oil and gas wells was treated inconsistently during HOLC neighborhood appraisals, with majority-White neighborhoods with racially restrictive covenants not being penalized for the presence of oil and gas wells, while neighborhoods with a majority of people of color were downgraded.[32]

The 2 measures of structural racism that we considered do not capture all forms of structural racism in the housing market, including block busting, restrictive covenants, urban renewal programs, or predatory lending. Nor do they capture other relevant dimensions of structural racism. For example, patterns of municipal annexation, including processes of “underbounding,” have often systematically excluded racially marginalized populations in unincorporated areas from public services, including drinking water provision.[33]

As water scarcity increases across the western United States, reliance on groundwater is projected to increase, and safeguarding groundwater quality will become even more critical to achieving California’s goal to ensure access to safe and affordable water as a human right.[34] The County and City of LA have recently passed ordinances to phase out existing oil and gas operations because of health concerns.[35] Study findings highlight the need to consider drinking water threats and possibly prioritize wells for closure and remediation in communities of color disproportionately impacted by fossil fuel extraction. AJPH

ABOUT THE AUTHORS

Alique G. Berberian and Lara J. Cushing are with the Department of Environmental Health Sciences, Fielding School of Public Health, University of California, Los Angeles (UCLA). Jenny Rempel and Nicholas Depsky are with the Energy and Resources Group, Rausser College of Natural Resources, University of California, Berkeley. Komal Bangia is with the Office of Environmental Health Hazard Assessment, California Environmental Protection Agency, Oakland. Sophia Wang is with the Institute of the Environment and Sustainability, UCLA.

CORRESPONDENCE

Correspondence should be sent to Lara J. Cushing, 650 Charles E Young Dr S, 71-259 CHS, Los Angeles, CA 90095 (e-mail: lcushing@ucla.edu). Reprints can be ordered at https://ajph.org by clicking the “Reprints” link.

PUBLICATION INFORMATION

Full Citation: Berberian AG, Rempel J, Depsky N, Bangia K, Wang S, Cushing LJ. Race, racism, and drinking water contamination risk from oil and gas wells in Los Angeles County, 2020. *Am J Public Health*. 2023;113(11):1191–1200.

Acceptance Date: June 23, 2023.

DOI: https://doi.org/10.2105/AJPH.2023.307374

CONTRIBUTORS

A. G. Berberian curated the data, conducted the analysis, prepared figures and tables, and wrote the original draft. J. Rempel provided redlining data and reviewed and edited the article. N. Depsky created the population sociodemographic estimates for community water systems and reviewed and edited the article. K. Bangia cleaned community water system boundaries and reviewed and edited the article. S. Wang assisted in data cleaning and analysis and reviewed and edited the article. L. J. Cushing originated the study, supervised the analysis, and reviewed and edited the article.

ACKNOWLEDGMENTS

This work was supported by the National Institute of Environmental Health Sciences (award P42ES004705), California Proposition 1 Sustainable Groundwater Planning Grant (award 4600012684), the UCLA Sustainable LA Grand Challenge, the Anthony and Jeanne Pritkzer Family Foundation, the JPB Environmental Health Fellowship, and the UCLA Fielding Presidential Chair in Health Equity.

We thank Clare Pace, Katherine Wolf, and Rachel Morello-Frosch (University of California Berkeley) for assistance in the curation of community water system data. We thank Felicia Federico (UCLA Institute of the Environment and

Sustainability) and Rita Kampalath (Los Angeles County Chief Sustainability Office) for helpful discussions on the methodology.

CONFLICTS OF INTEREST

All authors declare that they have no competing interests.

HUMAN PARTICIPANT PROTECTION

The study did not involve human participants.

REFERENCES

1. US Energy Information Administration. US Field Production of Crude Oil. 2022. Available at: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MCRFPUS2&f=M. Accessed July 3, 2022.
2. Czolowski ED, Santoro RL, Srebotnjak T, Shonkoff SBC. Toward consistent methodology to quantify populations in proximity to oil and gas development: a national spatial analysis and review. *Environ Health Perspect.* 2017;125(8):086004. https://doi.org/10.1289/EHP1535
3. McMahon PB, Barlow JRB, Engle MA, et al. Methane and benzene in drinking-water wells overlying the Eagle Ford, Fayetteville, and Haynesville shale hydrocarbon production areas. *Environ Sci Technol.* 2017;51(12):6727–6734. https://doi.org/10.1021/acs.est.7b00746
4. Kassotis CD, Vu DC, Vo PH, et al. Endocrine-disrupting activities and organic contaminants associated with oil and gas operations in Wyoming groundwater. *Arch Environ Contam Toxicol.* 2018;75(2):247–258. https://doi.org/10.1007/s00244-018-0521-2
5. Clark CJ, Xiong B, Soriano Jr MA, et al. Assessing unconventional oil and gas exposure in the Appalachian basin: comparison of exposure surrogates and residential drinking water measurements. *Environ Sci Technol.* 2022;56(2):1091–1103. https://doi.org/10.1021/acs.est.1c05081
6. California Department of Conservation. Idle well program. 2019. Available at: https://www.conservation.ca.gov/calgem/idle_well. Accessed July 4, 2022.
7. Chilingar GV, Endres B. Environmental hazards posed by the Los Angeles Basin urban oilfields: an historical perspective of lessons learned. *Env Geol.* 2005;47(2):302–317. https://doi.org/10.1007/s00254-004-1159-0
8. González DJX, Morton CM, Hill LAL, et al. Temporal trends of racial and socioeconomic disparities in population exposures to upstream oil and gas development in California. *GeoHealth.* 2023;7(3):e2022GH000690. https://doi.org/10.1029/2022GH000690
9. Sadd J, Shamasunder B. Oil extraction in Los Angeles: health, land use, and environmental justice consequences. In: Liberty Hill Foundation. Drilling down: the community consequences of expanded oil development in Los Angeles. 2015: 7–14. Available at: https://libertyhill-assets.s3-us-west-2.amazonaws.com/media/documents/Drilling_Down_Report_-_Full.pdf. Accessed July 3, 2022.
10. Gonzalez DJX, Nardone A, Nguyen AV, Morello-Frosch R, Casey JA. Historic redlining and the siting of oil and gas wells in the United States. *J Expo Sci Environ Epidemiol.* 2023;33(1):76–83. https://doi.org/10.1038/s41370-022-00434-9
11. California Department of Conservation. Monthly production data. Available at: https://filerequest.conservation.ca.gov. Accessed April 17, 2022.
12. Environmental Defense Fund. Filling the void: the value of new technology to reduce air pollution and improve information at oil and gas sites in California. 2017. Available at: https://www.edf.org/sites/default/files/california-monitoring_filling-the-void.pdf. Accessed July 5, 2022.
13. Pierce G, McCann H. Los Angeles County Community Water Systems: Atlas and Policy Guide. 2015. Available at: https://www.collinslaw.com/files/water_atlas_0.pdf. Accessed April 28, 2022.
14. Adkins-Jackson PB, Chantarat T, Bailey ZD, Ponce NA. Measuring structural racism: a guide for epidemiologists and other health researchers. *Am J Epidemiol.* 2022;191(4):539–547. https://doi.org/10.1093/aje/kwab239
15. California Department of Conservation, Geologic Energy Management Division. Oil and gas wells table, California. Available at: https://gis.conservation.ca.gov/portal/home/item.html?id=0d30c4d9ac8f4f84a53a145e7d68eb6b. Accessed April 17, 2022.
16. California State Water Resources Control Board. Drinking water—public water system information—California Open Data. Available at: https://data.ca.gov/dataset/drinking-water-public-water-system-information. Accessed April 17, 2022.
17. Tracking California. Water system service areas. Available at: https://trackingcalifornia.org/water-systems/water-systems-landing. Accessed April 17, 2022.
18. Pace C, Balazs C, Bangia K, et al. Inequities in drinking water quality among domestic well communities and community water systems, California, 2011–2019. *Am J Public Health.* 2022;112(1):88–97. https://doi.org/10.2105/AJPH.2021.306561
19. Nelson RK, Winling L, Marciano R, Connolly N. Mapping Inequality. *American Panorama.* Available at: https://dsl.richmond.edu/panorama/redlining. Accessed June 3, 2022.
20. Massey DS. The age of extremes: concentrated affluence and poverty in the twenty-first century. *Demography.* 1996;33(4):395–412, discussion 413–416. https://doi.org/10.2307/2061773
21. Krieger N, Waterman PD, Spasojevic J, Li W, Maduro G, Van Wye G. Public health monitoring of privilege and deprivation with the Index of Concentration at the Extremes. *Am J Public Health.* 2016;106(2):256–263. https://doi.org/10.2105/AJPH.2015.302955
22. Deddens JA, Petersen MR. Approaches for estimating prevalence ratios. *Occup Environ Med.* 2008;65(7):481, 501–506. https://doi.org/10.1136/oem.2007.034777
23. Zou G. A modified Poisson regression approach to prospective studies with binary data. *Am J Epidemiol.* 2004;159(7):702–706. https://doi.org/10.1093/aje/kwh090
24. Jasechko S, Perrone D. Hydraulic fracturing near domestic groundwater wells. *Proc Natl Acad Sci USA.* 2017;114(50):13138–13143. https://doi.org/10.1073/pnas.1701682114
25. Shonkoff SBC, Gautier D. A case study of the petroleum geological potential and potential public health risks associated with hydraulic fracturing and oil and gas development in the Los Angeles Basin. In: An Independent Scientific Assessment of Well Stimulation in California. Vol. III. Sacramento, CA: California Council on Science & Technology. 2015. Available at: http://ccst.us/publications/2015/vol-III-chapter-4.pdf. Accessed August 3, 2023.
26. Abdullah K, Malloy TF, Stenstrom MK, Suffet IH. Toxicity of acidization fluids used in California oil exploration. *Toxicol Environ Chem.* 2017;99(1):78–94. https://doi.org/10.1080/02772248.2016.1160285
27. Johnston JE, Chau K, Franklin M, Cushing L. Environmental justice dimensions of oil and gas flaring in South Texas: disproportionate exposure among Hispanic communities. *Environ Sci Technol.* 2020;54(10):6289–6298. https://doi.org/10.1021/acs.est.0c00410
28. Cushing LJ, Chau K, Franklin M, Johnston JE. Up in smoke: characterizing the population exposed to flaring from unconventional oil and gas development in the contiguous US. *Environ Res Lett.* 2021;16(3):034032. https://doi.org/10.1088/1748-9326/abd3d4
29. Swope CB, Hernandez D, Cushing LJ. The relationship of historical redlining with present-day neighborhood environmental and health outcomes: a scoping review and conceptual model. *J Urban Health.* 2022;99(6):959–983. https://doi.org/10.1007/s11524-022-00665-z
30. Silva GS, Warren JL, Deziel NC. Spatial modeling to identify sociodemographic predictors of hydraulic fracturing wastewater injection wells in Ohio census block groups. *Environ Health Perspect.* 2018;126(6):067008. https://doi.org/10.1289/EHP2663
31. Johnston JE, Werder E, Sebastian D. Wastewater disposal wells, fracking, and environmental injustice in southern Texas. *Am J Public Health.* 2016;106(3):550–556. https://doi.org/10.2105/AJPH.2015.303000
32. Cumming DG. Black gold, White power: mapping oil, real estate, and racial segregation in the Los Angeles Basin, 1900–1939. *Engag Sci Technol Soc.* 2018;4:85–110. https://doi.org/10.17351/ests2018.212
33. Balazs CL, Ray I. The drinking water disparities framework: on the origins and persistence of inequities in exposure. *Am J Public Health.* 2014;104(4):603–611. https://doi.org/10.2105/AJPH.2013.301664
34. Eng M. Assembly Bill No. 685 (2012). Available at: http://www.leginfo.ca.gov/pub/11-12/bill/asm/ab_0651-0700/ab_685_bill_20120925_chaptered.pdf. Accessed April 25, 2023.
35. Shamasunder B, Johnston J. LA's long, troubled history with urban oil drilling is nearing an end after years of health concerns. *The Conversation.* January 27, 2023. Available at: http://theconversation.com/las-long-troubled-history-with-urban-oil-drilling-is-nearing-an-end-after-years-of-health-concerns-198650. Accessed April 24, 2023.